KIMBROUGH, III, JAMES GRAY, Ph.D. Commuting, Gender, and Military Service: Three Essays in Applied Microeconomics. (2016)
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This dissertation uses applied microeconometrics to examine the economics of time allocation and human capital. To do so, these essays bring together data from a variety of sources, build theoretical economic models, and apply econometric methods to deal with empirical issues. In Chapter II, a new measure of commuting time for U.S. households is constructed by applying a previously developed methodology to a novel data source, the American Time Use Survey (ATUS). To assess the suitability of this new measure for empirical analysis, commuting times and patterns within the ATUS measure are then compared to those for commuting measures that have been constructed from other commonly used data sources. Chapter III takes advantage of this novel measure and associated ATUS data to investigate why women tend have shorter commutes than men. Previous studies have examined this "gender commuting gap," but have yet to provide a satisfying explanation. A theoretical economic model is developed here that generates predictions complementary to those in the literature. The empirical analysis that follows establishes that the measured gender gap is reduced when stops are included in the calculation of commuting times, but that the remaining gender difference in commuting time is related to gender differences in wages and the types of jobs held. Chapter IV applies econometric methods to a different empirical issue: the impact of military service in WWII and the Korean War on the educational attainment of children. Using U.S. Census data, this chapter constructs linked family data to find that a father's military service is associated with greater educational progress for his chil-

dren. Applying multiple methods to account for endogenous effects, the analysis is unable to reject the hypothesis that the observed relationship is due to endogeneity.

COMMUTING, GENDER, AND MILITARY SERVICE:

THREE ESSAYS IN APPLIED MICROECONOMICS

by

James Gray Kimbrough, III

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Approved by

____
Committee Chair

To my wife Holli, who remains supportive

despite that she is still waiting for me to be done so that I can clean the basement,

and our daughter Violet, who was no help whatsoever with the writing

but inspired me to complete this nonetheless.

APPROVAL PAGE

This dissertation written by James Gray Kimbrough, III has been approved by the following committee of the Faculty of The Graduate School at The University of North Carolina at Greensboro.

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CHAPTER I

INTRODUCTION

This dissertation uses the tools of applied microeconomics to investigate three dimensions of household decision-making and well-being: Chapter II examines how individuals commute between work and home; Chapter III investigated how commuting behavior differs by gender; and Chapter IV analyzes whether a father's military service has an impact on the subsequent educational achievement of his children. To examine such issues economists use three resources: theoretical models of individual and household behavior; data that document the characteristics of households, the decisions they make, and the environment in which they make them; and sophisticated empirical models that are used to examine hypotheses about household behavior. This dissertation contains all three of these components.

In Chapter II data from the American Time Use Survey (ATUS) offer the opportunity to examine commuting behavior and its relationship to demographics, labor market characteristics, and the amount of time spent on other activities. To do so, however, a previously developed methodology must be applied to this novel data source. Previous analyses have been complicated by the difficulties of obtaining commuting time measures from the ATUS. Travel information can be difficult to interpret in the ATUS, and many commuting trips are likely misclassified using stock measures of work-related travel. To address this shortcoming, Chapter II reviews the strategies of previous researchers to reclassify travel. After surveying possible approaches, a methodology that was developed for use with the National Household Transportation Survey (NHTS) is applied to the ATUS. Detailed time information in both the NHTS and the ATUS allows me to compare aggregate commuting measures and the timing of commuting in the two surveys. The analysis is further extended to compare to journey-to-work information in another commonly used dataset, the American Community Survey. These comparisons and the methodology provided serve to enable and validate further analysis of commuting behavior using the ATUS, leveraging the advantages of this dataset.

A wealth of research has shown that the commutes of American women are shorter, both in time and distance, than those of American men. Chapter III takes advantage of the ATUS data as developed in Chapter II to examine this relationship. To do so, a basic labor supply model is presented, with testable predictions about relationships between commuting time and worker characteristics that could explain the gender gap. Additionally, the detailed commuting characteristics derived from the ATUS permits the examination of differences in the character of commutes by gender, including the number, length, and type of stops along the way. Results show that women tend to make more stops between home and work, and that women are more likely to be accompanied by children for their commute even when controlling for marital status and the presence of children. Finally, it turns out that the stops made by women along a commuting journey tend to be longer than those for men, which indicates the importance of accounting for stop duration in the calculation of commuting time.

To test hypotheses from the literature and predictions of the theoretical model, multivariate models of commuting time as a function of worker characteristics are constructed. First, OLS models are estimated, containing a gender indicator to examine the gender gap remaining after controlling for these factors. Finally, Blinder-Oaxaca decompositions are performed to decompose the gender commuting gap by estimating a model in which these characteristics are fully interacted with gender. Results support multiple previously proposed explanations for the gender commuting gap: gender differences in wages and types of jobs held. The evidence does not suggest that women's greater household responsibility contributes to the gender commuting gap.

Chapter IV applies econometric tools to a different empirical issue, the impact of military service of fathers in WWII and the Korean War on the educational attainment of children. The American "high school movement" of the early 20th century resulted in a dramatic rise in high school graduation rates, a trend that continued into the middle of the century interrupted only by World War II. Previous work has characterized the pre-World War II transformation of secondary education, but less attention has been focused on the continued increase in educational attainment after the War. In fact, Baby Boomer children graduated from high school at a greater rate than any previous generation. The goal of Chapter IV is to assess whether whether and how the postwar surge in high school completion was associated with the high rates of military service by the parents of Baby Boomers or the post-service subsidies they received to increase their own education. Chapter IV links Baby Boomer children to their fathers using IPUMS data to examine this relationship. Through linear regression and propensity score matching, this analysis finds that father's veteran status is associated with greater educational attainment for children, particularly for WWII veterans. Exploiting discontinuities in military service allows for further examination of the exogeneity of this relationship, but the analysis does not provide strong evidence of whether the high school surge was due to the exogenous effect of military service and GI Bill subsidies rather than positive selection into military service.

CHAPTER II

COMMUTING IN THE AMERICAN TIME USE SURVEY

2.1 Introduction

Commuting plays a major role in the labor market decisions, time use, and satisfaction of many Americans. The commute acts as a fixed cost (in both time and money) to labor force participation. Commuting time limits the amount of time available for other activities. Length of commute can affect which jobs are available to job seekers, limiting potential labor markets. Additionally, commuting may play a significant role in happiness and satisfaction. Kahneman et al. (2004), for example, provide evidence that commuting ranks as one of the least desirable activities undertaken by workers. Because of these varied impacts on labor supply, location decisions, and general well-being, commuting has been the focus of study by a variety of researchers. Moreover, a range of studies has examined tradeoffs between time spent commuting and time spent on other activities. The scope of this research has been limited by the availability of a nationally representative survey with information on both commuting behavior and an array of other characteristics.

The American Time Use Survey (ATUS) collects extensive information on how Americans spend their time, including all episodes of travel time. While it does not distinguish between commuting and other travel episodes, it has advantages over other available datasets. The ATUS contains respondent characteristics that commonly used transportation datasets lack, such as wage and salary information. Moreover, unlike transportation surveys and other large surveys, the ATUS captures other uses of time on the same day. This includes the details of time spent on work, which could allow for further classifying commuting behavior. Furthermore, additional ATUS modules are available, making possible the use of data on other respondent characteristics such as eating and health information. The survey design also yields linkages to CPS panels with additional data.

Researchers have begun to use the ATUS for analyses of commuting behavior, though the commuting measures they have used have significant flaws. For example, DeLoach & Tiemann (2012) draw conclusions about the characteristics of commuting in the U.S. using an activity code that corresponds only partially to commuting. Christian (2012) exploits the unique advantages of the ATUS to examine tradeoffs between commuting time and time spent on health-related activities, but constructs a commuting measure which appears to overstate travel time.

For this analysis, commutes are defined generally as trips from home to work or from work to home. Classifying direct trips—with no stops along the way to perform any other tasks—as commuting is straightforward. Problems arise when an individual stops along the way between home and work, because it is not evident which of this travel is commuting and which is primarily intended to reach other destinations. McGuckin & Nakamoto (2004) develop and apply to the National Household Transportation Survey (NHTS) a methodology that addresses these chains of consecutive trips. They generate trip tours formed from linked trips that are anchored at home, work, and elsewhere, allowing for stops along the way of up to 30 minutes. Using this strategy, tours between home and work are treated as commutes.

The methodology of McGuckin & Nakamoto (2004) is applied to the ATUS to address its lack of an appropriate commuting measure. To do so, this requires accounting for several ways in which the information provided in the ATUS differs from that available in the NHTS. After applying this strategy, measured commuting in the ATUS is compared to that in the NHTS. Also, the estimates from the ATUS and NHTS are compared to those from a recall measure from the American Community Survey (ACS), a large, nationally representative yearly sample.

This paper begins with a description of the available nationally representative datasets used to examine commuting behavior. Next, possible methods of classifying travel are described, detailing the methodology developed in the transportation literature that is applied to the NHTS data to generate measures of commuting from complex chains of trips. This methodology is applied to ATUS data, examining the differences in commuting relative to other possible commuting measures. This then enables the comparison of estimates generated using this methodology from ATUS data to those generated using NHTS data as well as information from the ACS. The goal in the latter sections is to demonstrate the comparability of commuting estimates, providing evidence to support the use of this measure in a range of analyses. This measure will allow researchers to leverage the advantages of ATUS data while not differing markedly in travel classification methodology from analyses using NHTS data, and providing significantly more detail than analyses using ACS data.

2.2 Data

2.2.1 American Time Use Survey (ATUS)

The ATUS is an annual, national time use survey administered by the Bureau of Labor Statistics (BLS). One respondent per household is chosen from a subset of households which have recently completed the Current Population Survey (CPS). Begun in 2003, data are now available for years 2003 through 2013, with about 14,000 respondents per year. Response rates vary from 49.9% in 2013 to 57.8% in 2003. Weights are calculated to address varying nonresponse rates and oversampling of demographic groups and days of the week consistent with the stratified random sample design of the ATUS. These final ATUS respondent probability weights are used throughout this analysis to produce nationally representative estimates.

For each respondent, the survey collects time diary information on activities performed in a 24-hour period (from 4 AM the previous day to 4 AM the day of the interview) as well as a range of respondent and household characteristics. The time diaries are collected using "conversational interviewing," intended to help respondents generate time diaries through open-ended questions (Shelley, 2005). Each activity is then assigned an activity code based on the classification of the primary task being carried out. Information on those with whom the activity took place and the location (or for travel, mode) is also collected.

The reported and coded activities include travel episodes. ATUS respondents are not asked to provide the purpose of any trips, nor are they asked to identify travel specifically. Instead, a spell is coded as travel if it involves movement from one location to another. Overall, estimates of the total amount of time spent traveling in a day from the ATUS appear to be comparable to those using NHTS data, as demonstrated by Bose & Sharp (2005). However, classification of this travel time by its purpose is inexact.

The purpose of a travel spell is then coded on the basis of the activities taking place immediately before and after (Shelley, 2005). In general, travel is categorized as travel related to the next activity; the primary exception is travel to the respondent's home, which is classified as travel for the purpose of the previous activity. For example, if an individual reports that he watched TV, then drove his car, then shopped for groceries, this trip is classified as travel related to grocery shopping. If the next two activities he reports are driving followed by cooking at home, the second travel spell is also coded as travel related to grocery shopping.

The ATUS provides an activity code for "travel related to work."[1] Activities classified under this code meet one of two criteria:

(1) Travel occurring immediately before work activities, or

(2) Travel occurring immediately after work, provided that the next activity takes place at home.

This activity code does not correspond directly to commuting, differing in two main ways. First, because travel that is directly followed by work is generally coded as work-related travel, it contains some travel that is not commuting. For example, the return trip to work from an errand during the middle of the work day would in general be classified as travel related to work. Second, it does not include many commuting spells when stops are made along the way between home and work. Notably, this effect is asymmetrical, impacting the trip to work differently from the

[1] This corresponds to activity code 170501 in the 2003 ATUS and 180501 in subsequent years.

trip home. If a worker reports stopping to perform another activity along the way to work, only the last travel spell is generally coded as work-related travel. However, stopping on the way from work to home means that no travel from this commute leg is classified as travel related to work. Because of these shortcomings, this activity code is a poor proxy for commuting. Instead, this analysis proposes an alternate commuting measure, detailed below after a description of other datasets commonly used to examine commuting.

2.2.2 National Household Transportation Survey (NHTS)

The National Household Transportation Survey (NHTS) is a survey designed to provide nationally representative information on travel in the United States. The survey is performed periodically, most recently in 2001 and 2009. For direct comparison to the ATUS and ACS, this analysis focuses on the 2009 sample, which contains data collected from 150,147 households (U.S. Department of Transportation, Federal Highway Administration, 2011).

One major difference between the NHTS and the ATUS is that the NHTS seeks to interview every adult member of a surveyed household. While a household is considered "complete" for the purposes of inclusion in the final dataset if 50% of adult household members were interviewed, in practice 93% of eligible household members were interviewed either directly or, in a minority of cases, by proxy. These interviews covered travel days from March 28, 2008 to April 30, 2009. These dates are therefore not directly comparable to samples from the ACS and ATUS, but those samples are limited to the closest relevant year to approximate the travel period in question as closely as possible, the 2008 ATUS and 2009 ACS. As in both the ATUS and the ACS, person-level sampling weights are provided; these are used wherever appropriate.

In addition to a range of characteristics of interest to transportation planners, respondents provide a narrative version of a travel diary, giving information on all trips taken during a specified day. Similar to the ATUS, the NHTS contains information on trip purpose derived from the tasks performed before and after the trip was taken. As in the ATUS, determination of trip purpose is straightforward for direct trips, but more difficult whenever stops are made along the way. The NHTS data therefore have the same main drawback as the ATUS data for the purpose of studying commuting: there is no direct measure of commuting behavior, so an estimate of commuting must be derived in some way. One such methodology is used to assign trip tours to specific purposes, and this derived information is provided along with other NHTS data.

2.2.3 American Community Survey (ACS)

A third survey that is often used for its data on commuting behavior is the American Community Survey (ACS). The ACS is performed yearly by the Census Bureau, and samples 1% of households. In addition to the advantages of such a large, frequently repeated sample, it contains a host of demographic and economic information about respondent households and the individuals that comprise them.

However, the ACS contains only limited information on commuting. Respondents report the usual mode of travel to work, as well as information about the timing and duration of the trip to work. Specifically, respondents are asked, “How many minutes did it usually take this person to get from home to work last week?”

They are also asked, "What time did this person usually leave home to go to work last week?"

Respondents to the ACS are asked to recall information over a relatively long period and to average time over multiple commuting trips. Such information is likelyto be both less accurate and to reflect less variation than information for a single, recent commute captured by a travel or time diary. Moreover, the ACS does not capture time spent traveling home from work, and so may give an incomplete picture of commuting patterns. But the ACS information has the advantage that it focuses on travel from home to work to the exclusion of other activities. Because of this, it is a more direct measure of a portion of commuting behavior than the measures derived from ATUS and NHTS data, with several major caveats stemming from its construction using recall information about typical commuting to work in the past week.

2.3 Candidate Methodologies

The ATUS has many advantages for studying commuting behavior over other datasets, but lacks a satisfactory measure of commuting time. It is therefore necessary to construct such a measure from the ATUS diary data. Consistent with the broad conceptualization of commuting as travel between home and work, the candidate methodology should provide an estimate of actual time spent in such travel, but not traveling primarily for other reasons. Nonstop trips between home and work are easily classified. However, when a respondent makes stops along the way, properly classifying travel is difficult because of the lack of trip purpose information in the ATUS. The candidate methodology should consistently classify this travel as well.

2.3.1 Methodologies previously applied to the ATUS

Researchers have taken divergent approaches to measuring commuting in the ATUS. Some (for example, DeLoach & Tiemann (2012)) have used the ATUS measure of travel related to work, interpreting it as commuting. By design, this measure includes some travel that is not commuting and excludes many commuting travel spells. When commutes include stops for other activities along the way, a portion of the trip is not classified as travel related to work. Moreover, the treatment of trips with stops is asymmetric, with different classification results for travel to and from work.[2] For all of these reasons, travel between home and work is not consistently classified as travel related to work using this activity code.

Alternate approaches have attempted to reclassify travel between home and work to better measure commuting. Brown & Borisova (2007) propose such a methodology, which Christian (2012) adopts in an analysis of commuting and health-related activities. The authors consider all travel between home and work to be commuting, regardless of the number or length of stops. For individuals starting and ending at home, this can be thought to provide an upper bound of commuting time, but including all travel between the two likely substantially overestimates commuting time.

A modified version of the Brown and Borisova methodology is employed by Hamrick & Hopkins (2012) in an examination of travel to grocery stores. The authors calculate total travel between home and shopping, and between shopping and home, then take the minimum of the two travel times. This methodology does

[2] Additionally, a change in methodology between the 2003 and 2004 waves of the survey impacted which travel was classified as travel related to work. This is not a concern for the present analysis, since it focuses on other years of data, but is an issue with work using a range of years of ATUS data and relying upon the ATUS coding of travel related to work.

address the asymmetric nature of the ATUS travel measures. Applied to travel to and from work, it could be used to generate estimates of commute time. However, when a respondent made long stops in both directions between home and work, this travel would be included. In cases where no stops or only short stops are made, this method does not attempt to explain why one direction might take significantly longer than the other. If for example the time difference is due to normal traffic, this could underestimate commuting time.

2.3.2 Trip tour methodology

The trip tour methodology outlined by McGuckin & Nakamoto (2004) addresses the fundamental issue of assigning trip purpose to reported travel in trip chains. Classifying travel in this way necessitates the following terminology:

- *trip chains*: sequences of travel with stops;
- *trip tours*: trip chains that, following the McGuckin and Nakamoto methodology, contain stops of no more than 30 minutes; and
- *commuting trip tours*: trip tours that begin at home and end at work or begin at work and end at home.

All trips in a trip chain that contains stops of no more than 30 minutes each are combined to form tours anchored by home, work, or another location. Using this framework, commuting trip tours are those that either begin at home and end at work, or begin at work and end at home.

Tours are classified as occurring from home to work if the first trip begins at home, the last trip in the sequence ends at work, and the respondent does not report a dwell time of more than 30 minutes at any stop along the way. Tours beginning at home but ending with a 31 minute or longer stop somewhere other than work are classified as home-to-other. The same rules apply to trips from work to home. Therefore, this methodology classifies as commuting tours that contain no stop of more than 30 minutes and either begin at home and end at work or begin at work and end at home.

The Department of Transportation applies this methodology to the NHTS data to produce datasets containing information on trip tours, so that using this methodology allows for direct comparison to this large U.S. transportation behavior dataset. Some travel will likely be misclassified, but the 30 minute cutoff represents a reasonable attempt to balance misclassification in either direction. Other approaches may be more appropriate for classifying travel for other purposes, but focusing on commuting, it is sensible to allow for brief stops along the way but not longer dwell times.

In summary, two main methodologies have been previously applied to the ATUS. The "travel related to work" measure in the ATUS fails to capture significant amounts of commuting behavior. By contrast, including all travel between home and work, as in the Brown and Borisova measure, would be expected to classify too much travel as commuting. By allowing for relatively short stops along the way, the trip tour methodology represents a reasonable, though imperfect compromise. Subsequent sections examine how the differences among the three methodologies affect estimates of commuting behavior.

2.4 Applying the Trip Tour Methodology to the ATUS

A sample of respondents from the 2008 wave of the ATUS is used to apply the trip tour methodology to ATUS data while maintaining comparability to the NHTS sample.[3] The sample is limited to respondents between the ages of 25 and 60 who are employed.[4] Because work and commuting patterns differ significantly on weekends, the sample is limited to weekdays.

The commuting methodologies require information about the origin and destination of trips, based on the activities that precede and follow the travel spells. Therefore, it is necessary for these spells to have both activity information and location. However, ATUS respondents are not generally asked to provide a location for "personal care" activities, which include such common activities as sleeping, bathing, and grooming. This is of particular concern since many people, after waking in the morning, are likely to report only engaging in other personal care activities before leaving the house. Indeed, a sizable portion of this sample does not report an activity location before traveling in the morning. To address this all sleep spells occurring at the beginning and end of the ATUS diary day (that is, beginning before 4 A.M. or ending after 4 A.M.) are treated as occurring at the respondent's home. While this may misclassify the location of some sleep spells, it seems a reasonable assumption for the vast majority of respondents. To link this to the location of the respondent at the beginning or end of travel, is is further assumed that consecutive personal care spells with no intervening travel take place in the same location.

After supplying a location for these personal care activities, the sample is limited to those who begin and end the diary day at home. This produces a sample of

[3] Hierarchical extracts of ATUS data are obtained from the ATUS-X extract system (Hofferth et al., 2013). The 2008 ATUS is because the majority of diaries from the 2009 wave of the NHTS are for dates in 2008.

[4] The ATUS contains additional information on whether a respondent worked on a particular day, but this is not used here because such information is not available in the NHTS.

2,893 time diaries for individuals who are at home at 4 A.M. and return home by 4 A.M. The ATUS respondent probability weights are used to generate nationally representative statistics for these workers.

The simplest commutes to classify are direct trips from home to work or from work to home. These may contain multiple travel segments by different modes, but do not involve stops along the journey to perform other tasks. As shown in Table 1, the majority of workers have at least one nonstop commute trip during the day: 57% have at least one direct trip from home to work and 47% have a direct trip from work to home. However, only 37% have a commute on the diary day consisting of at least one direct trip from home to work and at least one direct trip from work to home.

Table 1. Commute Time and Incidence, ATUS Sample

	Mean time,	Percent of sample with trips:			
	minutes	To Work	To Home	Either	Both
Preferred Measure:					
Commuting trip tours	37.7	70.2%	60.5%	76.1%	54.7%
Other Measures:					
Nonstop commutes only	26.9	57.3%	46.8%	67.0%	37.1%
ATUS “travel related to work”	33.0	68.8%	54.4%	74.8%	49.2%
All travel between home and work	49.2	75.4%	76.1%	78.7%	73.0%

Notes: Trip tours are, as defined in McGuckin & Nakamoto (2004), chains of travel with no stop of more than thirty minutes. All travel between home and work includes all travel between the time a respondent is at home and at work, with no limitation on stop length. ATUS “travel related to work” is all travel with activity code 180501. Sample percentages are weighted using ATUS respondent probability weights.

Using the “travel related to work” code, somewhat more travel is classified as commuting. On average, respondents in the sample had 33 minutes of travel classified in the ATUS as “travel related to work.” As mentioned previously, this differs significantly from a measure of commuting trip tours. While it includes some travel that is not classified as commuting, overall this measure includes less travel than the commuting trip tour methodology. Primarily, this activity code does not include all travel when stops are made along the way. This is most pronounced in the to-home direction, with only 54% of the sample having travel classified as commuting to home using this measure.

An alternate method of accounting for trip chains is to include all travel between home and work, regardless of the length of stops along the way. This resembles the methodology proposed by Brown & Borisova (2007). As shown in Table 1, this measure generates a significantly larger estimate of commuting time than the trip tour methodology. This is consistent with the increase in number of commute trips in the NHTS when no limits on stop length are imposed, as shown by McGuckin & Nakamoto (2004).

Consistent with the trip tour methodology, consecutive travel spells are combined to form trip tours anchored by home, work, or other locations. Those tours with stops of more than 30 minutes somewhere other than home or work are excluded to generate a sample of commute tours, which are either home-to-work or work-to-home tours. Applying this methodology expands the proportion of the sample with commutes in each direction. The increase is slightly larger for the journey from home to work, with 70% of workers reporting at least one tour from home to work. Workers in the sample are more likely to stop on the way from work to home, and those stops are more likely to be greater than 30 minutes, so that only 61% of workers in this sample report trip tours from work to home.

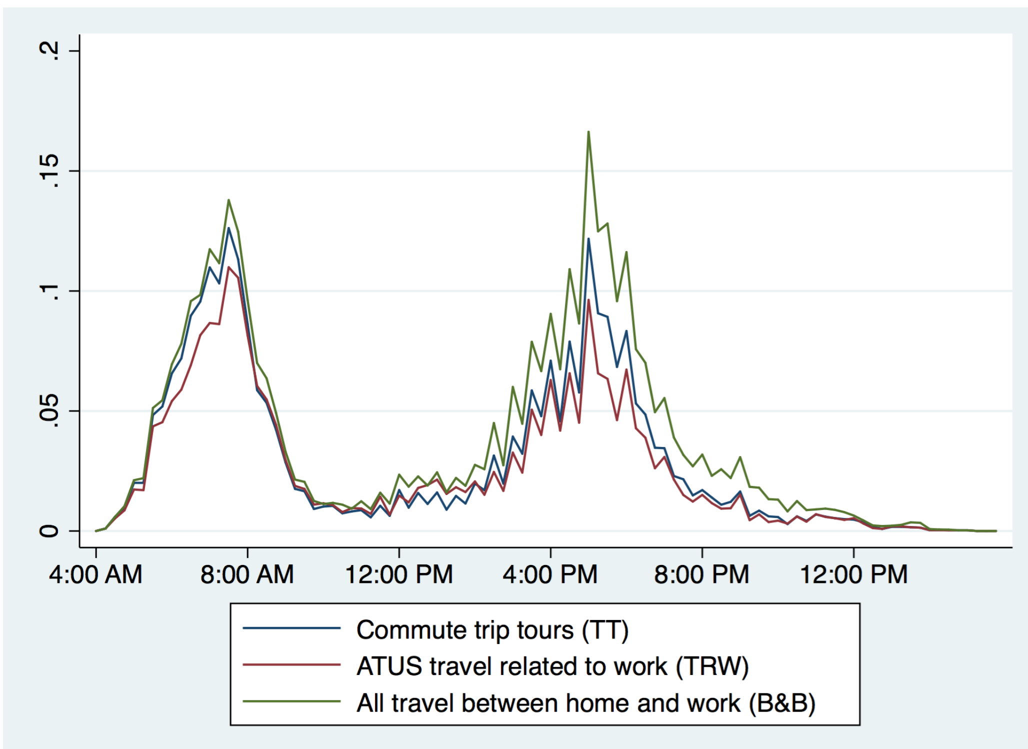
Using the definition of a commuting trip tour as any tour beginning at home and ending at work or beginning at work and ending at home, with stops for no more than 30 minutes, the average daily commuting time in this sample is 38 minutes. For comparison, including only nonstop commute trips between home and work yields an average commute of 27 minutes.

Table 1 also shows the impact of the different measures on the overall incidence of commuting. Using the trip tour methodology, 76% of individuals have some commuting travel. This is slightly more than the incidence of commuting measured using ATUS "travel related to work" (75%). 67% of individuals have a nonstop commute in at least one direction, while 79% have some travel between home and work.

Figure 1 shows the proportion of the ATUS sample commuting, based on three different methodologies, at 15 minute increments throughout the day. For all three measures, most commuting activity occurs, as expected, in the morning and early evening. The lines are more jagged in the late afternoon and evening, as respondents are more likely to be commuting on the hour and at 30 minutes past the hour than at 15 and 45 minutes past the hour. This appears to result from quite a few respondents reporting travel starting exactly at these times and ending at irregular times.

This illustration demonstrates how the distribution throughout the day of travel classified as commuting differs for the various measures. In general, commuting trip tours include more travel than the ATUS measure of travel related to work, with one notable exception in the middle of the day. This is expected, since some workers are traveling to or between work-related tasks at this time without going home. Such travel would not generate a trip tour between home and work but could be classified as travel related to work in the ATUS. The difference between commuting trip tours and travel related to work is most pronounced in the early morning and later evening. The morning difference is consistent with the ATUS travel related to work code excluding the first travel spell to work if a stop is made. Similarly, this measure excludes travel home from work where stops are made; this appears to be most common for workers commuting between 5:00 and 6:00 PM.

Figure 1. Proportion of Individuals Commuting at Times Throughout the Day, ATUS Sample



All travel between home and work includes only slightly more morning commuting than the commute trip tour measure, suggesting that few respondents are making stops longer than half an hour along the way to work in the morning. This difference is much more pronounced in the afternoon and evening, reflecting the greater tendency for workers to make long stops along the way home from work.

Table 2 details the differences in commuting incidence and time estimates using these three measures, both overall and by individual characteristics. In general, the trip tour methodology classifies as commuting more travel than the travel related to work measure, while less than the Brown and Borisova methodology. This is reflected in mean commuting time estimates, as well as commuting incidence (defined as the percent of respondents with any commuting) and two-way commuting incidence (defined as the percentage of respondents with commuting both to and from work on the given day). For the full sample, both the travel related to work and Brown and Borisova estimates of mean commuting time are statistically significantly different from the trip tour measure. This is shown in the rightmost columns of Table 2.

Statistically significant differences in estimates of commuting time persist for both measures over nearly all subgroups based on individual characteristics. Furthermore, these differences vary widely across some individual characteristics. For example, for men the trip tour methodology yields an additional 2.4 minutes of commuting time over the travel related to work measure. This difference is 7.2 minutes for women. The persistence of subgroup differences and the observed impact of the choice of measurement methodology on these differences underscore the need to choose an appropriate commuting measure, particularly for analyses of the relationship between commuting and individual characteristics.

For the example of gender commuting differences, the trip tour methodology represents a reasonable method of accounting for gender-based differences in the number of stops. The ATUS travel related to work measure excludes many commuting trips where stops are made. By contrast, classifying all travel between home and work as commuting allows for an unlimited number of stops of any length, which could overestimate the commuting time of women in particular. As it does for the entire sample, the trip tour methodology represents a reasonable attempt to balance misclassification in either direction to generate a preferred measure of gender differences in commuting.

Table 2. Results of Commuting Classification Using Three Methodologies

	Commuting incidence			Two-way commuting incidence			Mean commuting time, minutes			p-value of time difference relative to TT	
Characteristic	TT	TRW	B&B	TT	TRW	B&B	TT	TRW	B&B	TRW	B&B
Male	78.1%	77.7%	81.0%	58.1%	54.0%	74.7%	40.7	38.3	51.6	.004	<.001
Female	73.6%	71.3%	75.9%	50.7%	43.7%	71.0%	34.2	27.0	46.3	<.001	<.001
Less than high school	74.0%	68.3%	75.6%	54.0%	45.5%	68.7%	37.4	34.0	46.0	.099	<.001
High school graduate	76.0%	72.6%	77.4%	56.6%	48.9%	72.0%	33.8	28.6	41.6	<.001	<.001
Some college	74.5%	73.5%	77.3%	52.3%	45.0%	70.8%	36.4	30.6	49.2	<.001	<.001
College graduate	79.0%	79.3%	82.0%	55.8%	53.5%	77.4%	41.9	37.7	55.4	<.001	<.001
Graduate degree	75.0%	77.1%	79.6%	53.7%	52.0%	73.7%	39.9	36.8	54.0	.159	<.001
Age 25-34	78.2%	75.9%	80.4%	54.4%	47.6%	75.6%	39.8	33.6	51.7	<.001	<.001
Age 35-44	76.6%	75.8%	78.8%	56.8%	49.5%	73.6%	40.8	34.6	51.0	<.001	<.001
Age 45-60	74.3%	73.3%	77.4%	53.4%	50.0%	70.9%	34.3	31.7	46.3	.002	<.001
Non-Hispanic White	74.6%	73.9%	77.7%	53.2%	48.8%	72.3%	35.9	31.1	47.9	<.001	<.001
Other Race/Ethnicity	79.5%	76.9%	80.9%	58.2%	50.2%	74.6%	41.8	37.7	52.2	<.001	<.001
Full Sample	76.1%	74.8%	78.7%	54.7%	49.2%	73.0%	37.7	33.0	49.2	<.001	<.001

Notes: Sample of 2008 ATUS respondents. "TT" methodology is trip tour methodology as defined in McGuckin & Nakamoto (2004). "B&B" is Brown and Borisova methodology, i.e. all travel between home and work. "TRW" is ATUS "travel related to work," i.e. all travel with activity code 180501. Sample percentages and means are weighted using ATUS respondent probability weights.

2.5 Comparing Commuting in the ATUS, NHTS, and ACS

Applying the trip tour methodology to ATUS data has allowed for the construction of a preferred measure of commuting for the individuals in this sample, which should match the commuting measure available in the NHTS. Next, comparison samples of respondents are constructed, and observed commuting is compared across the surveys. The primary goal in this section is to demonstrate how closely the commuting tour methodology from the NHTS, when applied to the ATUS, reproduces the commuting behavior observed in the NHTS. Since the wealth of information in the ATUS makes possible many analyses that cannot be performed using the NHTS, establishing that the ATUS commuting measure is comparable to the NHTS commuting measure would enhance the credibility of these results. Where the two measures differ it is important to note and explain the differences. Additionally, since the ACS is also frequently used in analyses of commuting behavior, where possible estimates from ACS data are compared to those constructed from travel and time diaries.

The 2009 NHTS sample is limited to those between the ages of 25 and 60 who provided a travel diary for travel on a weekday. This is further limited to workers who begin and end the day at home. This sample should correspond to the sample of ATUS respondents constructed above.

First, aggregate commuting measures are compared in the NHTS and ATUS samples. Sample average commute times are summarized in Table 3. As shown here, the estimates of commuting time to work from the ATUS sample mirror those from the NHTS sample. Moreover, the estimates of to-work travel time from the ATUS and NHTS are close to those from the ACS when individuals reporting no commuting are excluded. This occurs at much greater frequency in the NHTS and ATUS than in the ACS. This is consistent with two major differences in the ACS. First, the ACS specifically asks respondents about usual travel time to work, encouraging them to report a non-zero amount. By contrast, the ATUS and NHTS do not ask separately about commuting, instead asking respondents to provide all activities or travel. Second, ACS respondents are asked to provide the usual travel time to work over the previous week, which would likely produce a non-zero response even if the respondent did not travel to work for some portion of the previous week. The ATUS and NHTS, by capturing only a single day, would yield more zero responses for such respondents.

Table 3. Average Commute Times in Minutes

	To-work travel		Total work travel	
Sample	Full sample	Excluding zeros	Full sample	Excluding zeros
ATUS	19.6	27.9	37.7	49.6
NHTS	18.5	28.6	37.0	55.2
ACS	25.0	26.1		

Notes: Samples are constructed using restrictions described in text, weighted using sample weights.

For total commuting, the ATUS mean time of 37.7 minutes is close to the NHTS mean time of 37.0 minutes. When individuals with zero commuting time are excluded, the means differ more significantly. This is a direct result of the higher incidence of commuting in the ATUS than in the NHTS, shown in Table 4. While a similar percentage of respondents in the two surveys have commuting travel both to and from work, the ATUS has a higher incidence of commuting in only one direction or the other. Because of this, 33% of NHTS respondents have zero commuting time, while only 24% of ATUS respondents lack commuting time.

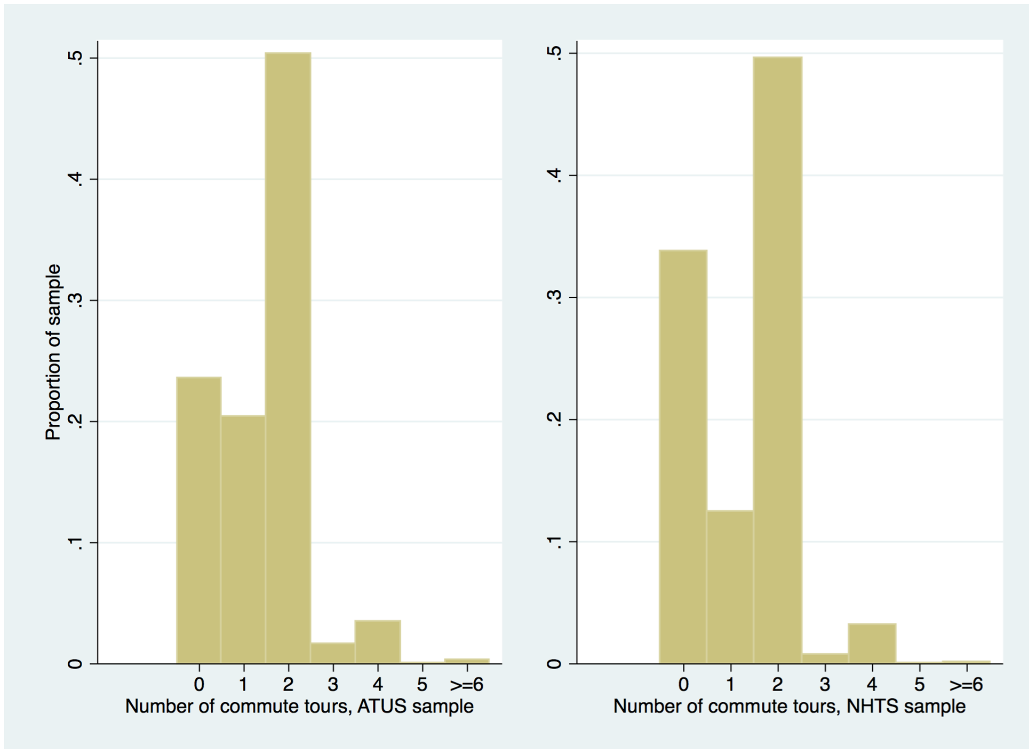
Table 4. Commute Time and Incidence

		Percent of sample with trips:			
Sample	Mean time, minutes	To Work	To Home	Either	Both
ATUS	37.7	70.2%	60.5%	76.1%	54.7%
NHTS	37.0	64.7%	56.8%	67.0%	54.5%
ACS		95.8%			

Notes: Samples are constructed using restrictions described in text; means and percentages are weighted using sample weights. The trip tour methodology was applied to both the ATUS and NHTS samples. ACS 1% sample from IPUMS (Ruggles et al., 2010).

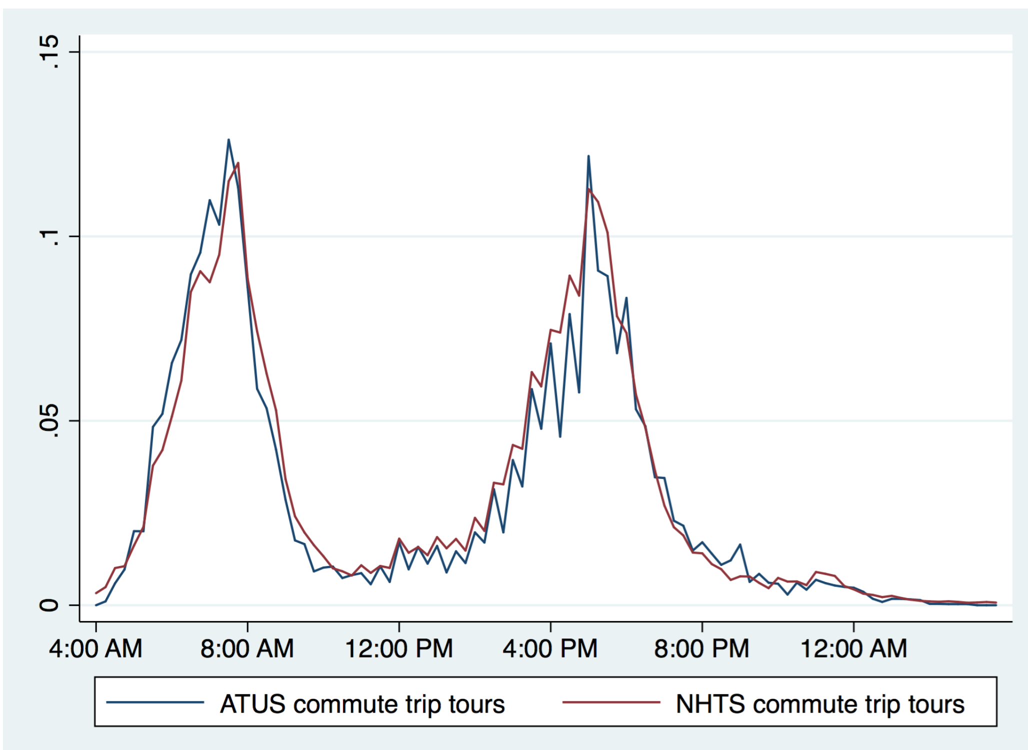
These differences are examined in a different way in Figure 2. Similar proportions of respondents report 2 or more commute tours in the NHTS and ATUS. However, significantly more ATUS respondents have a single commute tour; correspondingly, significantly fewer ATUS respondents have no commute tours. This is consistent with the results from Table 4 showing that more ATUS respondents have commuting in at least one direction, while similar numbers in the two surveys have commuting in both directions (roughly corresponding here to at least two commuting spells).

Figure 2. Distributions of Commute Tours, ATUS and NHTS Samples



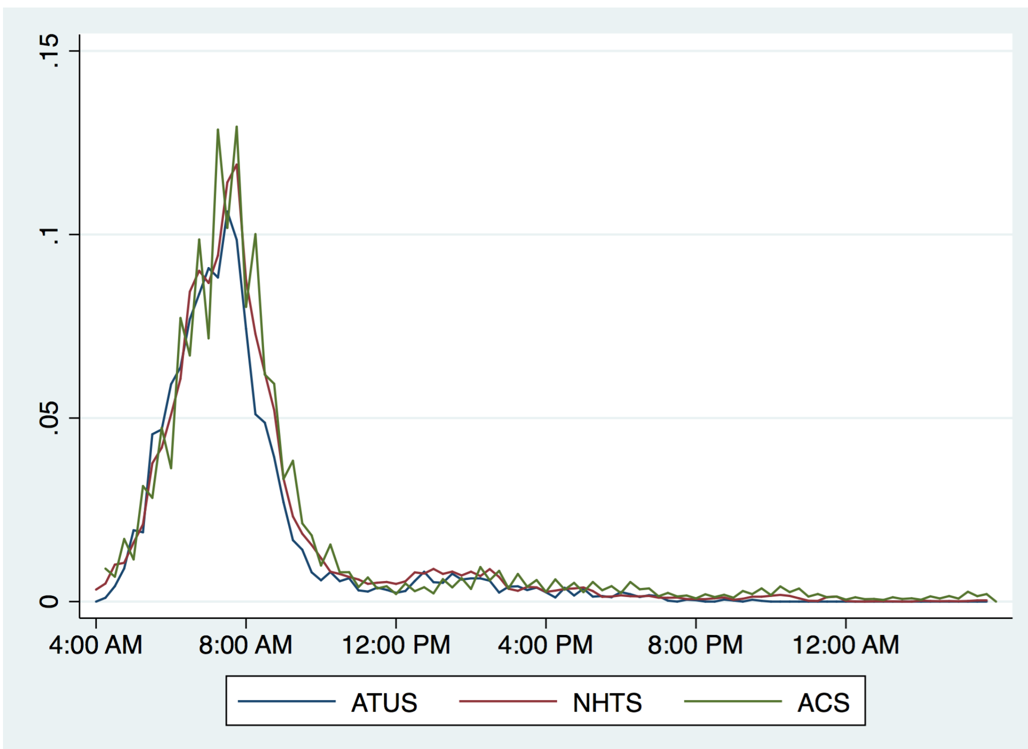
One major advantage of diary-based studies such as the ATUS and NHTS is that they make possible detailed analysis of the timing of activities. Because both the ATUS and NHTS provide the start and stop times for travel, it is possible to construct a figure analogous to Figure 1 displaying the distribution of commuting across the day for ATUS and NHTS respondents. This comparison, shown in Figure 3, shows the similarities in commuting travel captured by the trip tour methodology in the two samples. Overall, the two commuting profiles are very similar, though the ATUS sample appears to have slightly more travel classified as commuting in the morning and slightly less in the afternoon/evening. The ATUS profile has a more jagged appearance, a result of more respondents reporting commuting on the hour or at 30 minutes past the hour than at other times. For example, a rise in ATUS commuting at 4:00 is erased at 4:15, though exceeded by commuting at 4:30, followed by less commuting at 4:45. This appears to be a result of ATUS respondents tending to round the start times of their commutes to the nearest half hour. This effect is somewhat visible in the NHTS sample as well, but not to as great of an extent as in the ATUS.

Figure 3. Proportion of Individuals Commuting at Times Throughout the Day, ATUS and NHTS Samples



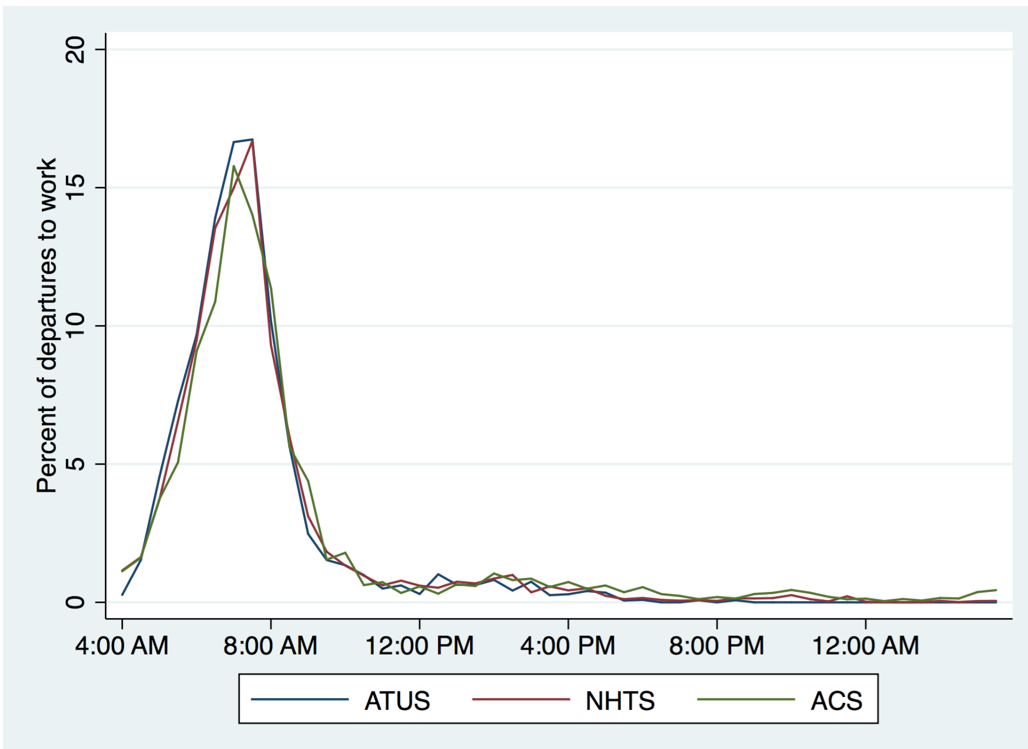
ACS respondents do not provide direct information on travel throughout the day. However, because the ACS collects information about the usual departure time in addition to the usual travel time to work, it is possible to compare ACS commuting behavior to work across the day to observed behavior using the commute tour methodology in the ATUS and NHTS. As shown in Figure 4, the three measures of commuting to work follow similar patterns. Each peaks with between about 11 and 13% of individuals commuting to work shortly before 8:00 AM. To-work commuting appears to occur slightly earlier in the ATUS, with the distribution shifted slightly to the left relative to the other two samples.

Figure 4. Proportion of Individuals Commuting to Work at Times Throughout the Day



Additionally, the information on usual departure time in the ACS can be compared to reported departure times in the ATUS and NHTS. For the ATUS and NHTS, this corresponds to the earliest start of a commute tour. As shown in Figure 5, the distributions of departure times appear to be similar in the three surveys. For example, in all three samples, about 15% of respondents report leaving for work between 7:00 and 7:29 AM.

Figure 5. Distribution of Departure Times to Work



In summary, when the commuting trip tour measure is applied to the ATUS, observed commuting behavior matches up closely with observed behavior in the NHTS, both in the aggregate (as shown by comparisons of means) and throughout the day (as shown by the above graph). This evidence supports the use of this methodology to produce measures of commuting that mirror those in the NHTS—an established survey used to produce reliable estimates of travel behavior—at the sample level. Moreover, measures of to-work commuting in the ATUS show similar patterns to those from the ACS, an additional large, nationally representative survey often used to study commuting.

2.6 Multivariate Analysis

The previous section established the consistency of the ATUS commuting trip tour estimates with the NHTS estimates in the aggregate and throughout the day. This section investigates similarities and differences in these two estimates related to individual characteristics. This analysis examines disaggregated commuting time estimates for multiple demographic characteristics for which it is possible to construct similar measures in the NHTS and ATUS.

These characteristics, and the proportion of each sample in a given subgroup, are shown in Table 5. The surveys contain comparable information on gender, educational attainment, and age. An indicator of whether an individual is a non-Hispanic white is also constructed for both surveys. Additional controls were examined, but either are not collected in both surveys or do not appear to be comparable.

As shown in Table 5, the samples are very similar in the percentage of respondents who are women (46%) or non-Hispanic whites (70%). The educational attainment profiles of the two samples are similar, though ATUS respondents are more likely to have a high school education or less, and less likely to have a graduate degree than their NHTS counterparts. The ATUS sample skews slightly younger than the NHTS sample, with more individuals 25-34 and fewer aged 35-44. This multivariate analysis allows this analysis to control for these differences at the individual level, to see whether these slight differences in samples might affect sample-level estimates.

Table 5. NHTS and ATUS Sample Characteristics

Characteristic	NHTS Sample	ATUS Sample
Gender		
Female	45.5%	46.3%
Education		
Less than high school	5.4%	9.0%
High school graduate	24.0%	26.1%
Some college	28.1%	25.6%
College graduate	25.2%	25.4%
Graduate degree	17.4%	13.9%
Age		
25-34	20.7%	27.9%
35-44	35.8%	28.9%
45-60	43.6%	43.4%
Race/Ethnicity		
White, non-Hispanic	69.5%	70.1%
Number of observations	75,570	2,893

Notes: 2008 ATUS and 2009 NHTS data with sample limitations in text. Proportions are weighted using sample weights.

To investigate disaggregated similarities and differences related to individual characteristics, the ATUS and NHTS data are pooled[5] and an OLS regression is estimated with commuting time as the dependent variable and a set of respondent characteristics as the independent variables. Specifically, the commuting time measure is calculated using the trip tour methodology, and the individual characteristics include indicators for gender, education level, and age brackets.

A regression is estimated with this suite of indicator variables, plus a set of interaction terms between these indicators and whether the reported time is from the ATUS. By performing an F-test on the estimated coefficients of these interaction

[5]Sample weights are used, corrected to give equal total weight to the ATUS and NHTS observations.

terms, it is possible to test whether there is a statistically significant association between a given characteristic and differences in calculated commuting time between the NHTS and ATUS.

The goal of this regression is to provide a detailed picture of the observable factors related to differences in calculated commuting time between the NHTS and ATUS. Effectively, this is an extension of simple t-tests of differences in commuting time by a single factor, such as gender. This t-test would be equivalent to performing the regression described above with only an indicator for women and the interaction of this indicator with an indicator for ATUS, then examining the t-statistic or f-statistic on the interaction term. The regression framework allows for the isolation of the relationship due to each factor by controlling for other observables.

The estimated coefficients are shown in Table 6, divided into three categories. The upper panel shows pooled characteristics; for example, women on average spend nearly 5 minutes fewer commuting than men, after controlling for all other factors in the regression. Similarly, high school graduates spend the most time commuting, on average—and those who have not graduated from high school spend the least time commuting—after accounting for all controls in the model.

Table 6. Multivariate Analysis Coefficient Estimates

Characteristic	Coefficient	Standard Error
Pooled Characteristics		
Female	-5.23	(0.86)
Less than high school	2.15	(2.28)
High school graduate	Omitted category	
Some college	0.61	(1.28)
College graduate	1.77	(1.25)
Graduate degree	0.53	(1.29)
Age 25-34	-1.92	(1.43)
Age 35-44	Omitted category	
Age 45-60	-3.78	(0.91)
White, non-Hispanic	Omitted category	
Other race/ethnicity	6.66	(1.07)
ATUS indicator	-0.92	(3.04)
Characteristics interacted with ATUS		
Female	-1.49	(2.00)
Less than high school	-2.70	(4.92)
High school graduate	Omitted category	
Some college	2.67	(2.77)
College graduate	6.98	(2.74)
Graduate degree	6.25	(3.41)
Age 25-34	0.64	(3.02)
Age 35-44	Omitted category	
Age 45-60	-1.54	(2.31)
White, non-Hispanic	Omitted category	
Other race/ethnicity	-0.17	(2.30)
Constant	38.48	(1.22)

Notes: 2008 ATUS and 2009 NHTS data with sample limitations in text. Dependent variable is commuting time in minutes.

The lower panel shows estimated effects for those characteristics interacted with whether respondents are from the ATUS. For example, on average women in the ATUS are estimated to spend nearly 2 minutes less commuting than women in the

NHTS, after controlling for the other factors shown. However, this effect is not statistically significant. Finally, the middle panel shows the estimated effect of measurement in the ATUS relative to measurement in the NHTS, after controlling for all pooled and interacted characteristics. This effect is small in magnitude and not statistically significant.

Table 7. Multivariate Analysis F-test Results

Characteristic	p-value
Pooled Characteristics	
Gender	<.001
Education Levels	.612
Age Brackets	<.001
White, non-Hispanic	<.001
ATUS indicator	.764
Interacted characteristics	
Gender × ATUS	.457
Education × ATUS	.047
Age × ATUS	.662
White, non-Hispanic × ATUS	.943
Total of ATUS indicator and interactions	.127

Notes: 2008 ATUS and 2009 NHTS data with sample limitations in text.

The f-test results from the regression are presented in Table 7. The upper panel provides evidence of strong relationships between gender and commuting time, and between age and commuting time. These relationships are expected and consistent with previous literature. Additionally, there is a statistically significant difference between commuting times for white, non-Hispanic respondents and others. Having controlled for these effects and their interactions, there is no significant difference remaining in expected commuting time between the ATUS and NHTS samples, as shown by the p-value of 0.764 on the ATUS indicator.

These results provide little evidence of gender- or age-based differences across the two samples. There is evidence of differences related to education levels (p-value of .05). This could suggest that education is measured differently in the two samples, or this relationship could mean that there are differences in how commuting time is captured for respondents of different education levels. However, the overall f-test of the ATUS indicator and all of its interactions does not provide strong evidence of differences in commuting time estimates related to this suite of factors. These commuting time estimates appear to be consistent across the samples not only at the aggregate level and across the day, but also across categories of basic demographics. One possible exception is education, which could warrant further examination.

2.7 Conclusions

Analysis of commuting behavior using the ATUS has been complicated by the difficulty of extracting detailed travel information from the survey data. This paper has provided a summary of these challenges and surveyed possible strategies for consistently measuring commuting using the available data. A methodology previously applied to the NHTS was selected which addresses many of the shortcomings of other possible measures. Estimates produced using this preferred methodology were compared to other measures that have been used previously, highlighting differences and the advantages of this measure. This analysis demonstrated the importance of methodology selection on observed differences across a range of individual characteristics.

Using this preferred methodology, calculated estimates were in line with those from the NHTS along multiple dimensions, including aggregate means, commuting incidence, and the distribution of commuting throughout the day. Further disaggregation of the estimates found only weak evidence of systematic differences between the measures from the ATUS and NHTS. The consistency of the estimates and multivariate results provide evidence that the trip tour methodology used on the NHTS can be similarly applied to the ATUS.

Therefore, this paper proposes the trip tour methodology as a strategy to produce consistent measures of commuting behavior in the ATUS for analyses where accurate measurement of commuting is a priority. Where there are stops between home and work, this methodology captures commuting in a consistent and reasonable way. It produces estimates consistent with those from the NHTS, a nationally representative, transportation-focused survey. And most importantly, applying the trip tour methodology to the ATUS allows for a wide range of analyses not possible with the NHTS or other commonly used travel surveys.

CHAPTER III

GENDER AND COMMUTING BEHAVIOR: EVIDENCE FROM THE AMERICAN TIME USE SURVEY

3.1 Introduction

Commuting plays an integral role in both labor force participation and the allocation of time to other activities. Moreover, the journey to work is unpleasant to many, ranking as one of the least desirable activities undertaken by workers (Kahneman et al., 2004). Many researchers have noted a gender gap in commuting: consistently, working women's trips to work are shorter in distance and time than those of their male counterparts. This gap persists despite major changes to women's labor market opportunities and the structure of American families.

The large, nationally representative survey datasets commonly used to examine this gap have significant drawbacks. This analysis utilizes a dataset that has not been used widely to study commuting behavior, the American Time Use Survey (ATUS). The ATUS collects extensive information on how Americans spend their time, including all episodes of travel time. While it does not distinguish between commuting and other travel episodes, it has advantages over other available datasets which are leveraged in this analysis. First, the ATUS contains some information on respondents' wage and salary, which many commonly used transportation datasets lack. Second, unlike other large surveys including those focused on transportation behavior, the ATUS captures other uses of time on the same day. This includes information about the activities individuals perform at stops along their journeys. Commuting behavior can be imputed using the method of Chapter II and combined with these additional characteristics to broaden the analysis beyond what is possible with other large datasets.

This analysis examines two dimensions of observed gender differences in commuting behavior that are revealed by the unique information available in the ATUS. First, I show that fundamental gender differences in the character of commuting arise because women are more likely to stop along the way between home and work. Second, I find that a gender gap in commuting time persists even when commutes are measured using a methodology that accounts for differences in stops along the way.

To investigate the second source of gender differences in commuting behavior, I examine hypotheses offered by previous researchers. To do so a standard labor supply model with fixed time costs of work is formalized. This structure predicts associations between commuting time and characteristics which differ significantly between women and men. These predictions, as well as suggested relationships from the literature, are tested in Sections 3.6 and 3.7. I find that gender differences in wages, non-labor income, and job characteristics all help to account for differences in commuting time not related to stops. There is no evidence, however, that the shorter commute times of women are related to greater levels of household responsibility.

3.2 Background

A variety of researchers have examined gender differences in American commuting behavior. MacDonald (1999) reviewed much of this research, finding consistent evidence that American working women have shorter commutes, in both distance and time, than their male counterparts. Surveying the variety of conclusions in this research, MacDonald offered four explanations for the gap.

First, women may have shorter commutes because their wages are lower than their male counterparts. Consistent with this explanation, Bianchi & Spain (1996) offered the explanation that jobs typically held by women offer a narrower range of pay than those more commonly held by men. Therefore, women receive less in return for taking on a longer commute than men. Examining data from Buffalo, New York, Johnston-Anumonwo (1997) indeed found a lower return to longer commutes for women.

A second explanation holds that women shorten their commutes to balance their dual roles as mothers and wage earners. For example, Hanson & Pratt (1995) found that women's household responsibilities constrained their job search and employment patterns, leading to shorter commutes. Moreover, this greater household responsibility may translate to more trips for non-work purposes. Along these lines, Rosenbloom (1995) analyzed the 1990 National Personal Transportation Survey (NPTS), concluding that women on average make more trips than men yet travel fewer miles, with these effects exacerbated by the presence of young children in the household.

A third explanation suggests that the types of jobs held by women are more likely to be closer to home. While occupational segregation has declined over time, significant gender differences in employment by industry and occupation remain. For many of the occupations and industries that employ women disproportionately, jobs are spread more even geographically. For example, Hanson & Pratt (1995) found that women working in male-dominated industries have similar commutes to men, while women in female-dominated industries have shorter commutes. This has been disputed by, for example, Gordon et al. (1989), who argue that the gender commuting gap persists across occupational categories. As noted by MacDonald (1999), this relationship remains uncertain.

Finally, a fourth explanation is that women have shorter commutes as a result of spatial entrapment in local labor markets. The spatial entrapment hypothesis holds that women are segmented into local labor markets, affecting job search and switching. This may be a larger factor for women than for men. For example, Hanson & Pratt (1988) found that women in their Worcester study sample are significantly more likely to choose employment based on their residential location than their male counterparts. However, this explanation is difficult to examine with the limited geographic data available in nationally representative datasets.

Since MacDonald's review, additional analyses have verified that the gender gap continues to persist across nationally representative datasets, including the 1995 National Personal Transportation Survey (Doyle & Taylor, 2000) and the 2005 American Housing Survey (Crane, 2007).

A related body of research has investigated the differences in how women and men commute. McGuckin & Murakami (1999) found, using travel diary data from the 1995 National Personal Transportation Survey (NPTS), that gender and family structure are strongly related to the number of stops made between home and work. Further refining a measure of trip tours to examine stops using the 1995 NPTS and 2001 National Household Transportation Survey (NHTS), McGuckin & Nakamoto (2004) settled on an operational definition allowing for stops of up to 30 minutes during a trip tour between home and work. Applying this measure to weekday workers in the 2001 NHTS, McGuckin et al. (2005) noted that women make more stops between home and work.

Chapter II applies this definition to ATUS data, detailing the methodology and establishing the comparability of commuting time estimates from the ATUS using this methodology to those from NHTS and American Community Survey (ACS) data. When the commuting trip tour measure is applied to the ATUS, observed commuting behavior matches up closely with observed behavior in the NHTS, both in the aggregate (as shown by comparisons of means) and throughout the day (as shown by the above graph). This evidence supports the use of this methodology to produce measures of commuting that mirror those in the NHTS–an established survey used to produce reliable estimates of travel behavior–at the sample level. Moreover, measures of to-work commuting in the ATUS show similar patterns to those from the ACS, an additional large, nationally representative survey often used to study commuting.

This measure retains the disadvantage that it is not derived directly from respondents. However, survey questions focused on commuting behavior can have their own disadvantages; for example, the ACS measures average commuting time to work over the past week. The derived ATUS measure, by contrast, allows for more flexible examination of travel to and from work across the entire day. Additionally, while it includes assumptions about the length of stops allowed along the way, this assumption can be relaxed, as shown in Section 3.5.

3.3 A Static Labor Supply Model of Commuting and Work

This proposed basic static model of labor and commuting decisions is intended to generate predictions about observed behavior. The basic model is motivated by an individual's decision whether or not to work when faced with a given job and its associated commute. In subsequent sections, the predictions of this model will be applied to ATUS data to decompose the relationships between gender, commuting time, and employee characteristics.

A commute functions as a fixed time cost of work, a basic extension of the simple static model of labor supply as explained by, for example, Killingsworth (1983). Utility is a general function of consumption (C) and leisure time (l). There are no monetary costs of work, and the only time cost of work is commuting (t); this cost is incurred only when an individual chooses to work. An individual maximizes her utility subject to a time budget constraint based on the choice of whether to work h hours:

$$T = h + t + l \tag{3.1}$$

If an individual chooses not to work, her utility is a function of consumption from non-labor income (N) and leisure time, equal to the total hours available (T):

$$U = W\left(N, T\right) \tag{3.2}$$

Where $W_N > 0$.

Her utility when she chooses to work is expressed as the indirect utility of working, a function of the wage w, non-labor income N, and commute time t (when she chooses the optimal number of hours to work):

$$U = V\left(w, N, t\right) \tag{3.3}$$

Where $V_w > 0$, $V_N > 0$, and $V_t < 0$.

In order for the individual to choose to work, the indirect utility of working must exceed the utility of not working. This condition is expressed through the function D, equal to the indirect utility of working minus the utility gained when not working:

$$D = V\left(w, N, t\right) - W\left(N, T\right) \tag{3.4}$$

An individual will choose to work when D is positive for a given bundle of w, N, and t. This can also be expressed in terms of the minimum wage and maximum commute that will make her at least indifferent between working and not working.

For a given N and T, the individual has a reservation wage $w^\star$ and a reservation commute time $t^\star$. She will choose to work only when the commute is equal to or less than the reservation commute, and only when the wage available is at least equal to the reservation wage.

Implicit differentiation gives the following conditions on $t^\star$:

$$\frac{\partial t^\star}{\partial w} = -\frac{\frac{\partial D}{\partial w}}{\frac{\partial D}{\partial t}} > 0 \tag{3.5}$$

$$\frac{\partial t^\star}{\partial N} = -\frac{\frac{\partial D}{\partial N}}{\frac{\partial D}{\partial t}} \begin{cases} > 0 & \text{if } \frac{\partial V}{\partial N} > \frac{\partial U}{\partial N} \\ < 0 & \text{if } \frac{\partial V}{\partial N} < \frac{\partial U}{\partial N} \end{cases} \tag{3.6}$$

The sign of $\partial t^* / \partial N$, ambiguous in Equation 3.6, can be determined due to differences in the marginal utility of non-labor income N in working and non-working states. Because a worker has wage income $w(T - l - t)$ in addition to non-labor income N, the marginal utility of non-labor income is lower than if she does not work, when her total income is only N. Therefore $W_N < V_N$. Since $W_N < V_N$, $\partial t^*/\partial N < 0$.

Lower reservation commutes translate to lower observed commuting time, since those with commutes higher than the reservation commute will choose not to work. Hence, under these plausible assumptions, the model yields two main predictions about relationships between commuting time and two underlying parameters, each of which might be expected to vary between men and women:

(1) A positive relationship between commuting time and the wage rate w, and

(2) A negative relationship between commuting time and non-labor income N.

As discussed in Section 3.2, numerous previous studies have explored the relationship between commuting time and wages. Since women in general earn lower wages than men, this has been a central explanation of the gender commuting gap, consistent with the predicted positive relationship between wages and commuting time. However, the nature of this relationship is less straightforward. One hypothesis is that the types of jobs women tend to hold systematically offer lower wages than the types of jobs held by their male counterparts.

The second relationship is more difficult to investigate. Like many datasets, the ATUS lacks detailed information on sources of income other than a respondent's wage income. However, for married individuals, a spouse's employment serves as a source of non-labor income. Married women's spouses are more likely to be employed than married men's spouses, so this would also be expected to shorten women's commutes relative to the commutes of men.

The following sections examine these predicted relationships, first descriptively and then using a variety of multivariate analyses. As detailed in Section 3.4.2, the ATUS contains no directly appropriate measure of non-labor income for all respondents, but does have a proxy for some individuals. Wage measures can be constructed for most ATUS respondents.

3.4 Data

This analysis uses American Time Use Survey (ATUS) data from 2003 to 2014 to examine the gender commuting gap.[1] The ATUS collects extensive information on how Americans spend their time, including all episodes of travel time, as well as a range of household and worker characteristics. The ATUS is an annual, national time use survey administered by the Bureau of Labor Statistics (BLS). One respondent per household is chosen from a subset of households which have recently completed the Current Population Survey (CPS). Begun in 2003, data are now available for years 2003 through 2014, with about 14,000 respondents per year. Response rates vary from 49.9% in 2013 to 57.8% in 2003. Respondent probability weights are used to account for nonresponse and oversampling of some groups, producing nationally representative estimates.

The ATUS collects extensive information on how Americans spend their time, including all episodes of travel time. While it does not distinguish between commuting and other travel episodes, it has advantages over other available datasets. The ATUS contains respondent characteristics that commonly used transportation datasets like the NHTS lack, such as wage and salary information. Moreover, unlike

[1] I use hierarchical extracts of ATUS data obtained from the ATUS-X extract system (Hofferth *et al.* 2013)

both the NHTS and the ACS, the ATUS captures other uses of time on the same day. This includes details of time spent at stops along the way between home and work. This allows for examination of stops along journeys, including the number, type, and length of these stops. Such analysis is not possible with the ACS, and while the NHTS contains some information about the number of stops, it does not provide the extensive detail about type and length of stops available in the ATUS. Finally, the ATUS contains information on who is present for each activity, important for examining whether women are more likely to be accompanied by children while traveling.

For each respondent, the survey collects time diary information on activities performed in a 24-hour period (from 4 AM the previous day to 4 AM the day of the interview) as well as a range of respondent and household characteristics. The time diaries are collected using "conversational interviewing," intended to help respondents generate time diaries through open-ended questions (Shelley 2005). Each activity is then assigned an activity code based on the classification of the primary task being carried out. Information on those with whom the activity took place and the location (or, for travel, mode) is also collected.

The reported and coded activities include travel episodes. ATUS respondents are not asked to provide the purpose of any trips, nor are they asked to identify travel specifically. Instead, a spell is coded as travel if it involves movement from one location to another. Overall, estimates of the total amount of time spent traveling in a day from the ATUS appear to be comparable to those using NHTS data, as demonstrated by Bose and Sharp (2005). However, classification of this travel time by its purpose is inexact.

The purpose of a travel spell is then coded on the basis of the activities taking place immediately before and after (Shelley 2005). As detailed in Chapter II, using this ATUS classification of travel is unsatisfactory, especially when examining groups which systematically differ in the number of stops along the way between home and work. As shown in Section 3.5, this holds for gender in the sample examined.

3.4.1 Trip Tours

The trip tour methodology outlined by McGuckin & Nakamoto (2004) addresses the fundamental issue of assigning trip purpose to reported travel in trip chains. Classifying travel in this way necessitates the following terminology:

- *trip chains*: sequences of travel with stops;
- *trip tours*: trip chains that, following the McGuckin and Nakamoto methodology, contain stops of no more than 30 minutes; and
- *commuting trip tours*: trip tours that begin at home and end at work or begin at work and end at home.

All trips in a trip chain containing stops of no more than 30 minutes each are combined to form tours anchored by home, work, or another location. Using this framework, commuting trip tours are those that either begin at home and end at work, or begin at work and end at home.

Tours are classified as occurring from home to work if the first trip begins at home, the last trip in the sequence ends at work, and the respondent does not report a dwell time of more than 30 minutes at any stop along the way. Tours beginning at home but ending with a 31 minute or longer stop somewhere other than work are classified as home-to-other. The same rules apply to trips from work to home. Therefore, this methodology classifies trips as commuting tours that contain no stop of more than 30 minutes and either begin at home and end at work or begin at work and end at home.

This methodology is applied to the ATUS data, as outlined in Chapter II. A threshold for allowed stop time of 30 minutes is chosen, as proposed by McGuckin and Nakamoto. However, to explore the impact of including different length stops on the gender gap, this threshold is adjusted for some analyses in Section 3.5.

3.4.2 Analysis Dataset Construction

Few measures of wages and income are included in the ATUS. Hourly earnings information is included for less than half of the respondents in this sample, since it is only available for those who report hourly earnings. For the remainder of the sample, information on weekly earnings and the usual weekly number of hours worked is available. These data are used to construct hourly wages for those individuals who do not report hourly wages. If the usual number of hours worked in a week is not reported, this analysis uses 40 hours per week for those reporting full time work and 20 hours for those reporting part time work. Wages are adjusted for inflation using the Consumer Price Index for Urban consumers (CPI-U) to 2003 dollars. Individuals whose constructed hourly wages are less than \$5 or greater than \$200 are then excluded. Finally, the log of hourly wages is used in all subsequent multivariate analyses.

One proxy for non-labor income is the presence of an employed spouse. For married individuals, an employed spouse represents a source of income independent of the individual's labor market decisions. This proxy is used to explore the predicted relationship between non-labor income (N) and commuting time. Additional family characteristic indicators are constructed for the presence of children and whether a household child was present for any part of the commute.

Individual controls for age and white non-Hispanic status, as shown in Table 8, are included in these analyses. Additionally, indicator variables for metropolitan status are constructed. Unfortunately, geographic information is not available for all respondents, so the metropolitan status variable can take on one of five values. For 121 individuals, metropolitan status is not identified at all. 3,220 individuals are identified as in a metropolitan area, with no information about whether they are in the central city. All other respondents are classified as outside of a metropolitan area or within a metropolitan area and residing either in the central city or in the balance of the metropolitan area.

Controls for factors that affect the segment of the labor market faced by the respondent are also constructed. In addition to indicator variables for the highest level of education completed, indicators for each of 22 occupation categories and 21 industry categories are used to control for the occupation and industry of the respondent's main job. The sample distributions of these occupations and industries are shown in Appendix Table 24.

3.4.3 Sample Characteristics

ATUS data are limited in that they contain information only on a single day for each respondent. The analysis is limited to respondents who work full time and report working on the diary day. Additionally, evidence from Giménez et al. (2015) suggests that the self-employed differ significantly from employed individuals, both theoretically and empirically. The self-employed are also much less likely to have valid wage values in the ATUS. For these reasons, self-employed respondents are excluded.

Furthermore, to produce a sample that most closely resembles normal working days, it is limited to diary days that are non-holiday weekdays. Only individuals who are between the ages of 25 and 60 are examined, using ATUS data collected from 2003 to 2014. Finally, in constructing the commuting measure the sample is limited to those beginning and ending the day at home.[2] The resulting sample contains 21,564 individuals: 11,344 men and 10,220 women. For all analyses, these observations are weighted using ATUS respondent probability weights.

As shown in Table 8, men represent 57% of the weighted sample. Women in the sample are less likely to have a spouse or child present in the household than their male counterparts. Women in the sample tend to be slightly older and more educated than sampled men.

[2]As described in Chapter II, sleep spells beginning and ending the diary day (which have no associated location) are recoded as taking place at home.

Table 8. Sample Characteristics

	Full Sample	Men	Women
Male	56.8%	100%	0%
Female	43.2%	0%	100%
Less than high school	6.9%	8.9%	4.3%
High school graduate	26.9%	28.5%	24.8%
Some college	25.6%	23.6%	28.2%
College graduate	25.5%	24.7%	26.6%
Graduate degree	15.1%	14.2%	16.2%
Age 25-34	29.0%	29.5%	28.3%
Age 35-44	29.3%	30.0%	28.2%
Age 45-60	41.8%	40.5%	43.5%
Non-Hispanic white	70.1%	70.3%	69.8%
Other race/ethnicity	29.9%	29.7%	30.2%
Child present in household	45.9%	47.6%	43.6%
No children present	54.1%	52.4%	56.4%
Spouse present	64.6%	68.6%	59.3%
Unmarried partner present	5.4%	5.1%	5.7%
No spouse/unmarried partner	30.0%	26.2%	35.0%
Metropolitan, central city	25.6%	25.2%	26.0%
Metropolitan, balance of MSA	44.1%	44.5%	43.5%
Metropolitan, not identified	14.7%	15.0%	15.4%
Nonmetropolitan	14.8%	15.0%	14.5%
Metropolitan status not identified	0.6%	0.6%	0.6%
Number of Observations	21,564	11,344	10,220

Source: ATUS 2003-2014 samples with restrictions as noted in text. Sample percentages are weighted using ATUS respondent probability weights.

3.5 Gender Differences in Commute Character

The commutes of men and women in the sample differ in multiple ways. First, men's mean commutes are significantly longer: men commute 54.6 minutes on average, while women commute 49.2 minutes on average. Differences in mean times will be explored and decomposed further in section 3.6.

Table 9. Stops of up to 30 Minutes Along the Commute

	Mean number of stops		% of gender sample	
	Men	Women	Men	Women
Child present in household	0.51	0.94	47.6%	43.6%
No child present in household	0.37	0.39	52.4%	56.4%
Child present on commute	0.93	1.32	16.6%	27.2%
No child present on commute	0.34	0.37	83.4%	72.8%
All	0.43	0.63	100%	100%

In addition, men and women show significantly different characteristics of stops between home and work. As shown in Table 9, using the adapted McGuckin and Nakamoto commute tour measure allowing for stops of up to 30 minutes, women on average make 0.63 stops along the commute in a day while men make an average of 0.43 stops. Men and women without children in the household make about the same number of stops, 0.37 for men and 0.39 for women. However, women in the sample with children in the household make an average of 0.94 stops, significantly more than men in the sample with household children, who average 0.51 stops. The difference is concentrated among those whose children are present on at least part of the commute. While 44% of women have household children compared to 48% of men, only 17% of men in the sample are joined by a child for at least part of the commute, compared to 27% of women. The increased propensity for stops is concentrated in these individuals; on average, men joined by children along the commute make 0.93 stops and women with children present make 1.32 stops.

Table 10 summarizes the prevalence of the most common stop purposes for those in the sample who stop along the way between home and work. Women are significantly more likely to make stops for the purpose of caring for and helping household members. Combined with their greater propensity to make stops along the way, this underscores the far greater responsibility of caring for household members taken on by women in the sample.

Table 10. Primary Stop Activities for Stops of up to 30 Minutes Along the Commute

	% of sample with primary Stop	
	Men	Women
Caring for and helping household members	26.0%	42.5%
Consumer purchases	35.4%	27.8%
Caring for and helping non-household members	6.9%	4.9%
Socializing, relaxation, and leisure	4.5%	2.9%
Eating and drinking	4.2%	1.0%
Other	23.0%	20.9%

Women in the sample are significantly more likely to stop along the way between home and work, with 38% stopping at least once, compared to 29% of men. As shown in Table 11, more women than men make 2 or more stops: 16.4% of women versus 9.5% of men. These differences in stop behavior translate, on average, into an addition 0.2 stops per day for women, and an additional 2.1 minutes per day spent at stops along the commute.

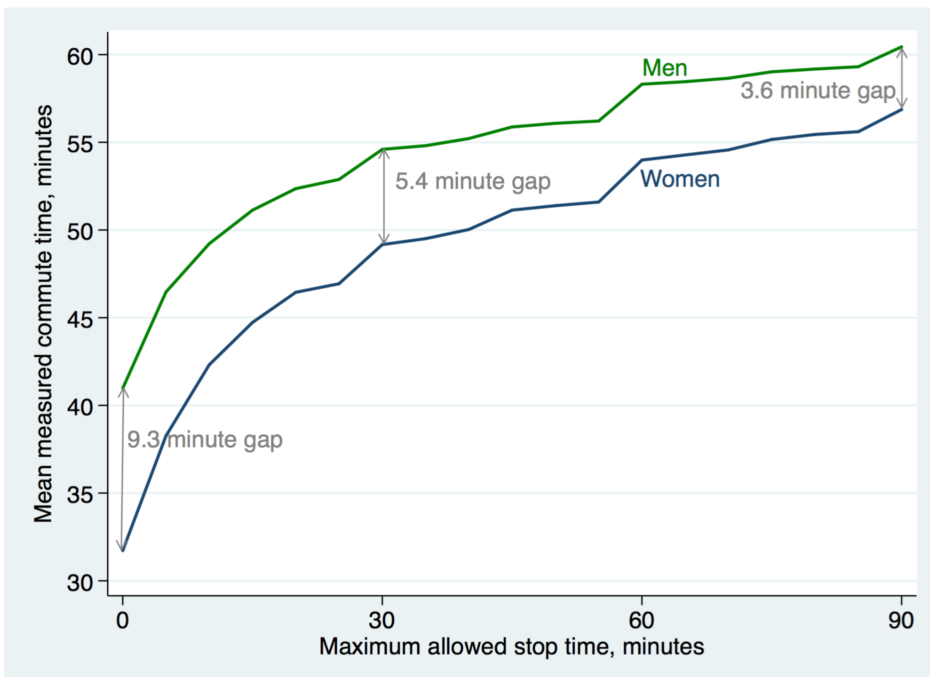
Table 11. Characteristics of Stops of up to 30 Minutes by Gender

	Men	Women
% of sample with stops along day's commute tours:		
0 stops	71.3%	61.8%
1 stop	19.2%	21.8%
2 stops	6.4%	11.1%
3 or more stops	3.1%	5.3%
Mean number of stops	0.43	0.63
Mean time spent at stops, minutes	4.8	6.9

Tables 10 and 11 use a reasonable threshold of 30 minutes for stops along the commute; allowing for stops of up to 30 minutes, women make significantly more stops and spend longer at these stops than men. Women in the sample also have more stops of longer duration than their male counterparts; if the threshold is relaxed to include more of these stops, the gender gap in commuting time shrinks. Figure 6 plots mean commute time for men and women when the maximum allowed stop time is increased in five-minute increments. If no stops are allowed along the commute, the average gap is 9.3 minutes, falling to 5.4 minutes with up to 30 minute stops and to 3.6 minutes with stops of up to 90 minutes allowed. This underscores the importance of using a commuting measure that accommodates some stops along the way.

In summary, women are more likely to stop along the journey between home and work. The gender difference is concentrated in those who have a child present for at least part of the commute. Women are almost twice as likely as men to fall in this category, and women who commute with children make even more stops than men who commute with children. This is consistent with women's higher propensity to stop for purposes related to child care. As a result, the gender commuting gap is highly sensitive to whether the commuting measure accommodates stops along the way. This analysis therefore relies on the commuting calculation methodology from Chapter II as a reasonable means of allowing for shorter stops along the commute.

Figure 6. Allowing Longer Stops Decreases the Gender Commuting Time Gap



Source: ATUS 2003-2014 samples with restrictions as noted in text, weighted using ATUS respondent probability weights.

3.6 Descriptive Analysis

The weighted mean commuting time for men in the sample is 54.6 minutes, compared to 49.2 minutes for women. These times are significantly higher than those shown in Table 2 of Chapter II due to additional sample restrictions used in this analysis. First, because the previous analysis was for comparison to NHTS data, it omitted two restrictions that are not possible using the NHTS: excluding holidays and limiting to workers working at a job outside of the home on the survey day. More significantly, this sample is limited to full-time employees who are not self-employed. These additional sample restrictions raise the mean observed commuting times by about 15 minutes.

The gap in commuting time for men and women, while a modest 5.4 minutes, represents 10% of the mean male commute and is statistically significant. This descriptive analysis focuses on two predicted effects from the theoretical model presented in Section 3.3. First, individuals with higher wages are predicted to have higher commuting times. Second, those with higher non-labor income are predicted to have lower commuting times. Due to a lack of detailed income information, the only available proxy for non-labor income is (for married individuals) whether a spouse is employed.

3.6.1 Wages

The commuting time gap between women and men is roughly constant across the wage distribution. As one illustration, individuals were ordered by wage and assigned to five quintiles, each containing 20% of workers. As shown in the top panel of Table 12, higher wages are associated with longer commutes for both men and women. However, the gender gap persists when comparing men and women at any of five wage quantiles, holding constant at about four minutes. Moreover, women are more likely to be in the three lower quintiles; 67.6% of women have wages of $19.19 or less while only 54.3% of men do. The within-quintile gap of approximately four minutes combines with different wage distributions for men and women to yield a larger overall gap of 5.4 minutes.

Table 12. Respondent Characteristics and Commuting Time

	% of gender sample		Mean commuting time	
	Men	Women	Men	Women
Quintile wage range, 2003 dollars				
$5.00-$10.50	17.2%	23.8%	47.2	43.4
$10.51-$14.42	18.2%	22.4%	50.2	45.5
$14.43-$19.19	19.0%	21.4%	54.1	50.9
$19.20-$27.30	21.5%	18.0%	56.6	52.7
≥$27.31	24.2%	14.4%	61.8	57.4
Spouse characteristics				
Spouse present and employed	51.5%	55.9%	55.3	50.0
Spouse present but not employed	22.3%	9.1%	58.7	47.2
No spouse present	26.2%	35.0%	49.7	48.4
Household children				
Children in the household	47.6%	43.6%	57.7	52.7
No children in the household	52.4%	56.4%	51.7	46.4
Commuting with children				
Child present for commute	16.6%	27.2%	59.7	56.2
No child present during commute	83.4%	72.8%	53.6	46.5
Total	100%	100%	54.6	49.2

Notes: ATUS 2003-2014 samples with restrictions as noted in text. Means are weighted using ATUS respondent probability weights. Each wage quintile contains approximately 20% of the sample sorted by wage.

3.6.2 Presence of Employed Spouse

As shown in Table 12, more women than men in this sample have an employed spouse present. For men, having an employed spouse present is associated with a decreased commuting time relative to an unemployed spouse. This is consistent with the predicted negative relationship between N and reservation commute.

However, for women the effect is reversed, and an employed spouse is associated with a longer commute than an unemployed spouse. This could be due to the confounding effects of household children. While 53% of women with unemployed spouses have children under 18 present, 65% of those with employed spouses do. By contrast, this is reversed for men, who are about 9% more likely to have a child present if their spouse is unemployed.

3.6.3 Presence of Children

An array of prior studies have suggested that women's greater household responsibilities play a role in their shorter commutes. Section 3.5 examined how these responsibilities impact the number of stops made along the way. Those who commute with a child are much more likely to stop along the way. While this holds true (at least in part) for both men and women, women are much more likely to have a child present for at least part of the commute.

When commuting time is calculated using the trip tour methodology allowing for stops up to 30 minutes, children are associated with longer commutes for both women and men, as shown in Table 12. This association holds both for the presence of children in the household and for children present for at least part of the commute. Moreover, more men than women in the sample have a child present in the household and on the commute. So while responsibility for children is associated with more stops along the way between home and work, it also seems to be associated with longer commutes. Therefore, this relationship does not help to explain the shorter commutes of women.

3.7 Multivariate Analysis

To further explore the relationship between individual characteristics and commuting time, multivariate models of commuting time as a function of worker characteristics are constructed. First, OLS models containing a gender indicator are estimated to examine the remaining gender gap after controlling for these factors. All multivariate OLS models regress total work-related travel time for an individual on a $female$ indicator and a host of controls.

Estimated coefficients for four models with progressively more controls are shown in Table 13. The gender gap remains statistically different from zero at the 5% level in all models. The gap shrinks markedly when wage, spouse, child, and education controls are added in Models (2) and (3). It is reduced further by the addition of indicators for occupation and industry in Model (4). Controlling for other factors in the model, women are estimated to spend 5.4 fewer minutes commuting in Model (1), about between 3.1 and 3.4 fewer minutes in Models (2) and (3), and 1.6 fewer minutes in Model (4).

Table 13. Linear Regression Coefficient Estimates

	Model			
	(1)	(2)	(3)	(4)
Characteristic				
Female	-5.44 (0.70)	-3.09 (0.71)	-3.43 (0.70)	-1.64 (0.77)
White, non-Hispanic	-4.60 (0.80)	-6.45 (0.83)	-4.23 (0.95)	-4.39 (0.95)
Log wage		11.30 (0.78)	8.87 (0.81)	6.56 (0.86)
Spouse present		2.76 (1.18)	3.13 (1.17)	2.68 (1.15)
Spouse employed		-1.05 (1.04)	-0.76 (1.01)	-0.27 (0.99)
Child present in HH		4.53 (0.77)	4.68 (0.75)	4.80 (0.75)
Indicators				
Year	Yes	Yes	Yes	Yes
Age	Yes	Yes	Yes	Yes
Education	No	Yes	Yes	Yes
Metropolitan status	No	No	Yes	Yes
State	No	No	Yes	Yes
Occupation	No	No	No	Yes
Industry	No	No	No	Yes

Notes: OLS regressions estimated using ATUS 2003-2014 samples with restrictions as noted in text, weighted using ATUS respondent probability weights. Standard errors are in parentheses.

As predicted by the theoretical model in Section 3.3, log wages are positively associated with commuting time. Similarly, the sign of the effect of an employed spouse for married workers is negative (as predicted), though this effect is not statistically significant. However, much of the gender commuting gap remains in Model (3), even after controlling for wages, spousal employment, the presence of children, and a host of other controls. Model (4) adds controls for industry and occupation, lowering the estimated effect of wages on commuting time and reducing the remaining gender gap significantly. This is consistent with the hypothesis that one component of women's lower observed wages is associated with gender differences in occupation and industry of employment. This is also consistent with the explanation from MacDonald (1999) that the types of jobs women hold are more likely to be closer to home.

Next, Blinder-Oaxaca decompositions (Blinder, 1973; Oaxaca, 1973) are estimated using a model in which these characteristics are fully interacted with gender. This generates estimates of the proportion of the gap that is (1) associated with differences in covariates, (2) associated with differences in the effects of these covariates, and (3) associated with the interaction of differing characteristics and differing effects.

As shown in Table 14, these results suggest that across models, differences in observed characteristics explain only between 30% and 39% of the commuting gap. When controls for industry and occupation are excluded as in Models (2) and (3), almost all of the remaining difference is associated with gender differences in the impact of observed variation. For Model (4), almost a third of the gap is estimated to be associated with the interaction of differences in observed characteristics and differences in the impact of those characteristics. Because the difference between this model and Model (3) is the addition of industry and occupation characteristics, the differential impact of these job characteristics (combined with differences between men and women in industry and occupation) may be driving a significant portion of the gender commuting gap. However, the estimated effects in Model (4) are significant at the 10% level but not at the 5% level.

Table 14. Blinder-Oaxaca Decomposition Results

	Model		
	(2)	(3)	(4)
Difference	5.43	5.43	5.43
Associated with differences in:			
Observed characteristics	2.12	1.62	2.16
	(0.33)	(0.35)	(0.92)
Coefficients	3.00	3.28	1.75
	(0.72)	(0.71)	(0.91)
Interaction of observed characteristics and coefficients	0.31	0.53	1.52
	(0.44)	(0.44)	(1.16)

Notes: Blinder-Oaxaca decompositions estimated using ATUS 2003-2014 samples with restrictions as noted in text, weighted using ATUS respondent probability weights. Models include the same characteristics as models 2-4 in Table 13. Standard errors are in parentheses.

Consistent with the OLS results, the Blinder-Oaxaca decomposition results suggest that gender differences in wages and household characteristics explain some (about 1/3) of the gender gap. Much of the remaining gap is associated with the interaction of gender differences in observable characteristics–especially occupation and industry of employment–and gender differences in the impact of those characteristics.

Like the OLS results, these results are consistent with the predictions of the theoretical model: a positive association of wages and negative association of spousal employment and commuting time. Moreover, these results are consistent with two of the explanations for the gender gap offered by MacDonald (1999): women's lower wages, and the more even distribution of jobs that hire women.

3.8 Conclusions

The persistent gender gap in commuting has been the subject of an array of previous studies. This analysis has used a novel data source, the ATUS, that allows for the examination of aspects of commuting character as well as overall commuting time. Women are more likely to make stops along the way between home and work. They are also more likely to stop for purposes related to child care, consistent with the explanation that women have more household responsibility than men.

Descriptive and multivariate analysis suggests that, largely consistent with the implications of a simple static labor supply model, differences in wages and non-labor income explain a significant proportion of the gender gap. Another large portion of this gap may be explained by differences in job characteristics, as well as the differential impact of those characteristics for women and men. Combined with the previous picture of differences in commuting character, these analyses provide evidence to support two of the explanations that MacDonald (1999) offers for the wage gap:

- Women's low wages
- The more even distribution of jobs that hire women

The impact of differences in distribution of jobs that hire women appears to be felt not directly but through an interaction with differences in the impact of these job characteristics for women. Additionally, spatial entrapment in local labor markets may play a role, but cannot be examined using the ATUS data.

However, this cross-sectional analysis is not able to identify a relationship between greater household responsibility and shorter commutes. Indeed, the presence of children–and in particular children brought along on the commute–is associated with longer commutes for both women and men when commuting time is calculated using a method that allows for brief stops along the way. Such a relationship may be identifiable using longitudinal data, but this study finds no evidence of a role for women's household responsibility in explaining the gender commuting gap.

CHAPTER IV

THE EDUCATIONAL LEGACY OF THE GREATEST GENERATION: PATERNAL MILITARY SERVICE AND BABY BOOMER EDUCATIONAL PROGRESS

4.1 Introduction

Baby Boomers, defined by the U.S. Census Bureau as those born between 1946 and 1964, attained higher levels of education than any preceding generation. Their experiences and outcomes were shaped by the experiences of their parents; one particularly major experience shared by many fathers of Baby Boomer children was military service. War itself directly shaped the lives of many, but it had additional long-lasting effects as well. After World War II, an array of programs sought to aid the veterans whose children would form the Baby Boomer generation. Legislation that would become known as the GI Bill created two major benefits for veterans: subsidies for postsecondary education and a loan program allowing eligible veterans to obtain mortgages with little or no down payment and at favorable interest rates. Previous work has demonstrated that veterans took advantage of these programs in large numbers, and has provided strong evidence that these incentives had corresponding effects on their own educational attainment and homeownership. In turn, significant bodies of literature have provided evidence that parental education and homeownersip have a positive impact on their children's educational attainment.

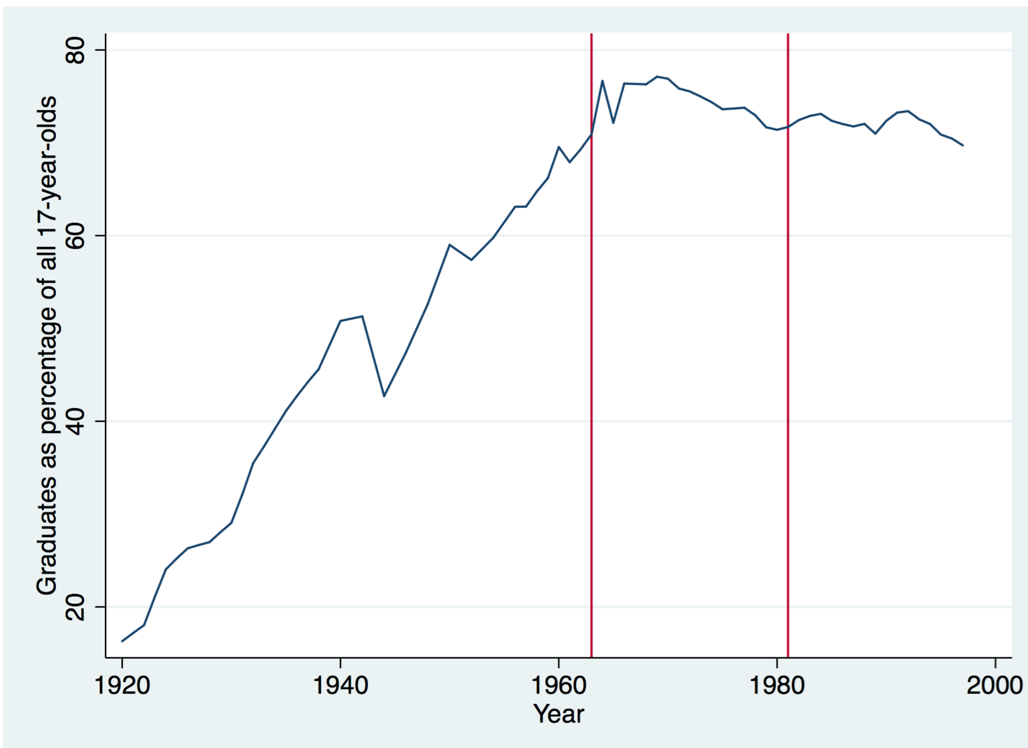
The prevalence of military service among the fathers of Baby Boomer children, the demonstrated impact of programs for veterans on fathers' education and homeownership, and evidence of intergenerational effects of these characteristics suggest that military service may have played a role in increasing the educational attainment of Baby Boomer children. This paper therefore seeks to answer two questions. First, is there evidence that the continuing gain in educational attainment for those born after World War II is related to fathers' military service? Second, if there is a relationship, is this a causal relationship due to either military service itself or the benefits that were associated with it, or is it related to positive selection into the service during World War II and the Korean War?

This analysis confronts the challenge of finding appropriate intergenerational data to examine the basic relationship between a father's military service and the educational attainment of his Boomer children. A significant positive relationship is established using linear probability models, and this relationship is verified using an alternative technique, propensity score matching. Next, this analysis attempts to answer the question of the role of selection in this relationship. A review of the ways in which previous studies of veteran effects have addressed selection into military service in this time period is used to establish the strategy implemented here to account for selection. Results suggest that while evidence of a significant relationship is present, the current methods are not able to provide a convincing answer to the question of whether this is due to selection into military service.

4.2 Historical Context

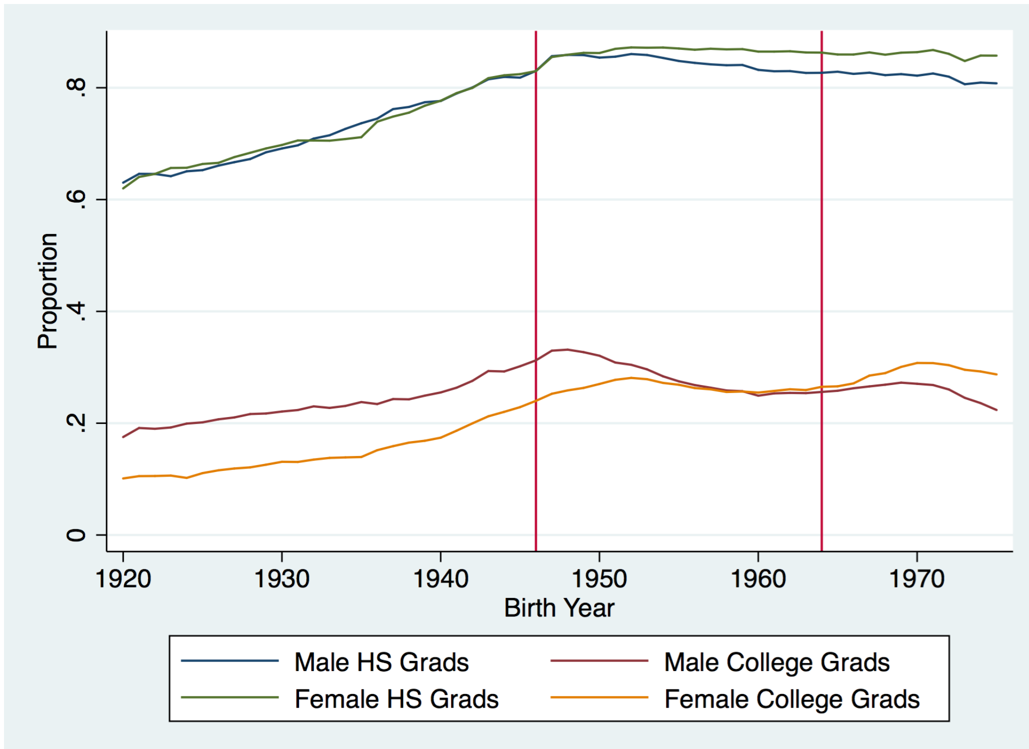
Secondary schooling in the United States underwent a rapid transformation from 1910 to 1940 as the "high school movement" led to a dramatic increase in high school enrollment and graduation (Goldin, 1998; Goldin & Katz, 1999). This rapid rise in high school graduation, unique to the United States in this period, is evident in Figure 7. The graduation measure shown in Figure 7, calculated by Goldin (2006) as the proportion of high school graduates divided by all 17 year olds in a year, continued its steady rise until World War II. Less examined is the continuation of this expansion in secondary schooling in the postwar period well after the high school movement. Graduation rates continued to increase steadily for successive cohorts through the Baby Boomers.

Figure 7. Proportion of 17 Year Olds Graduating from High School



Source: Goldin (2006). Vertical lines correspond to cohort boundaries of Baby Boomers.

Figure 8. Proportion of Individuals Graduated from High School and College, 2000



Source: 2000 IPUMS 5% sample (Ruggles 2010). Vertical lines correspond to cohort boundaries of Baby Boomers.

Retrospective Census data from 2000 in Figure 8 tell a similar story, with cohort high school graduation rates rising for both men and women through those born in the late 1940s. Still other measures of high school graduation by Heckman & LaFontaine (2010) show the same pattern, with the graduation rate peaking in the early 1970s, corresponding to those born in the early to mid 1950s. This continued rise and subsequent plateau of graduation rates helped Baby Boomers attain a higher level of educational attainment than previous generations.

Multiple factors could explain the greater educational attainment of Baby Boomer children. Clearly, the greater educational attainment of the parents of Baby Boomers–

those taking part in the rapid rise in secondary school enrollment during the high school movement–would be expected to play a role in increasing children's educational attainment. While previous research has struggled to identify effects of exogenous variation in parental education on children's educational attainment, Oreopoulos et al. (2006) have exploited variation in compulsory schooling laws as a source of such variation. To the extent that increasingly educated cohorts of parents come about through similar mechanisms, their results suggest that positive effects on children's educational progress would be expected.

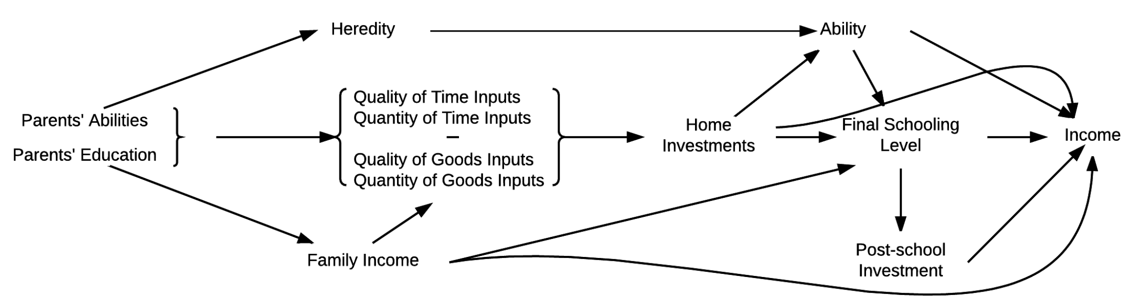
But education was not the only parental characteristic undergoing dramatic change in the post-World War II period. As the nation rapidly suburbanized in the mid-20th century, the homeownership rate rose dramatically. Indeed, for white households the homeownership rate increased from 42% in 1940 to 64% in 1960 (Carter et al., 2006). As with parental education, a growing body of research has shown that homeownership can affect child outcomes. For example, Haurin et al. (2002) find that children living in owned homes have greater math and reading achievement and lower incidence of behavioral problems than their counterparts in rented homes. Similarly, Green & White (1997) and Aaronson (2000) find that parental homeownership is associated with greater educational attainment for children. Hence, the substantial increase in homeownership might also have played a role in increasing educational attainment of Baby Boomer children.

The legislation which would come to be known as the GI Bill, intended to aid the reintegration of World War II veterans (and later, veterans of other conflicts), notably subsidized both homeownership and postsecondary schooling for veterans. The latter was accomplished through scholarships and stipends for veterans attending college, while homeownership was encouraged through the establishment of the VA loan program. Through this program veterans could obtain mortgages, often with preferential interest rates and generally with little or no down payment. Previous research has shown that veterans took advantage of these incentives, providing evidence that they led to significant increases in educational attainment and homeownership among veterans. Work by Bound & Turner (2002) and Stanley (2003) has demonstrated effects of GI Bill incentives on veterans' postsecondary educational attainment, while Yamashita (2008) and Fetter (2013) have estimated sizable impacts of the VA loan program on veteran homeownership. Analyzing the effect of these programs on the children of veterans, however, requires the construction of an appropriate dataset linking fathers to children.

4.3 Determinants of Children's Attainment

Figure 9, adapted from a review of the literature by Haveman & Wolfe (1995), provides an illustration of possible pathways impacting children's attainment.

Figure 9. Economic Model of Home Investments in Children and their Impacts on Children's Attainments, adapted from Haveman & Wolfe (1995)



4.3.1 Parental education

Parental education would be expected to impact a child's educational outcomes in multiple ways. First, as illustrated in Figure 9, increasing parental education is associated with increasing family income, which in turn can increase the quality and quantity of goods inputs (in particular) to home production and can have a direct impact on children's educational attaiment. Additional evidence from Guryan et al. (2008) also suggests that greater parental education is associated with more time spent with children, providing a possible relationship between parental education and the quantity of time inputs as well.

4.3.2 Homeownership

Haurin et al. (2002) propose two possible primary mechanisms for homeownership to affect children's educational outcomes:

> We suggest two mechanisms, one being the stronger investment incentive of owners compared with renters, the other being greater geographic stability. The investment incentive should result in a homeowner having a better home environment, and we argue that good home environments positively impact child outcomes. The greater stability of homeowners suggests that homeowners will develop greater social capital in their neighborhood. Also, children will be exposed to a more stable school environment. We again expect a positive impact on child outcomes.

Homeownership represented an extremely significant mechanism for building wealth in the latter half of the 20th century, aided by significant subsidies for homeownership in the United States. As a result, the first mechanism is difficult to disentangle from direct financial effects.

Neighborhood effects are similarly difficult to disentangle from other impacts of homeownership, particularly since datasets with excellent information on educational outcomes or progress and other necessary controls generally do not contain highly specific geographic information. Haurin et al. (2002) use county-level controls, but this analysis makes no attempt to control for neighborhood characteristics since no such data are available in the Census samples used.

The existing literature does not appear to suggest that these underlying mechanisms have changed from the 1960s to the 1980s. This might be of greater concern in using samples from earlier Census years, but the 1970 samples used in this analysis include children born 1955 and later. Homeownership increased rapidly during and immediately after the war, from 43.6% in 1940 to 55.0% in 1950. But it then increased more gradually–to 61.9% in 1960 and 62.1% in 1970–and remained under 65% through 1990.[1] Veterans could still have enjoyed the wealth-building effects of homeownership, but the impact of neighborhood effects on children would not have begun until the children were born.

More recent studies by Barker & Miller (2009) and Holupka & Newman (2012) have called into question the relationship between homeownership and children's educational outcomes, suggesting that the observed relationship could merely be due to selection into homeownership. Holupka and Newman make a particularly strong case that the homeownership effect is due to selection; if this is in fact the case, then controlling for homeownership in this analysis could bias estimates of other effects downward. Therefore, models are estimated with varying sets of controls where appropriate.

[1]Homeownership rates are taken from Carter et al. (2006), Series Dc745, 4-507.

4.3.3 Paternal military service

Parental military service could affect children's educational outcomes through three possible mechanisms other than parental education and homeownership:

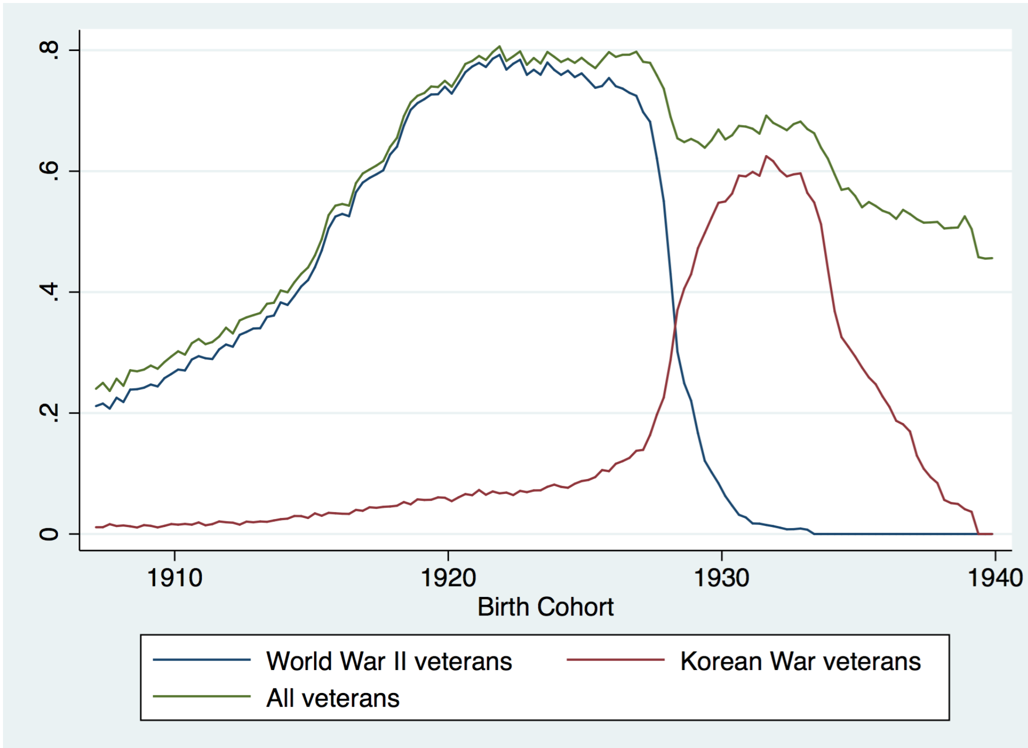
(1) A father's unobserved characteristics (loosely, "ability") could be conferred to his children through heredity.

(2) Unobserved preferences of the father could affect allocation of resources (that is, the quantity and quality of inputs) to children.

(3) The father's ability could modify the effects of his education on his children.

The first two pathways appear to be indistinguishable empirically. Broadly speaking, there could be certain characteristics of veteran fathers that are either passed on to children (through genetic or environmental means) or that affect how these fathers are as parents, with lasting impacts on their children. In previous studies that have attempted to identify impacts of military service using similar data, the primary concern has been that men self-selected or were selected into military service for reasons that could be related to such unobservable characteristics. One additional possible wrinkle might be the third pathway above: there might be something about selection into military service that amplifies the effect of education, above and beyond the direct pathways through which nonrandom selection directly impacts children's educational progress. This interaction could be due either to unobservable father characteristics, or due to the impact of military service itself. The regression discontinuity estimation strategy does not allow for investigation of such an interaction effect.

Figure 10. Proportion of White Male Birth Cohort Serving in the Military



Source: 1970 IPUMS Form 2 samples, pooled to create a nationally representative 3% sample of respondents. Cohorts contain all white males with unallocated values for veteran status variables.

4.4 Service in WWII and the Korean War

As shown in Figure 10, the vast majority of white men born in draft-eligible years served in World War II.[2] Similarly, large proportions of some cohorts served in the Korean War, though the draft was shorter-lived and less widespread than the draft for World War II.

Angrist & Krueger (1994) provide an overview of the system used to draft men into service for World War II. In their analysis, they focus on the second part of

[2]Notably, however, the majority of those men were not involved in combat; Stouffer et al. (1949) estimate that one fourth of those serving in World War II served in combat.

the sixth registration, covering men born in 1925 onward. During this period, the likelihood of being drafted into service was based entirely on birthdate; moreover, voluntary enlistment was prohibited. Where young drafted men obtained deferments, this was most likely for reason of physical or mental disability (Bound & Turner, 2002). As such, those who served in WWII were generally more physically and mentally able than their counterparts who did not serve.

A similar draft system was carried through for service in the Korean War (Bound & Turner, 2002), with birthdate continuing to be the strongest predictor of service. However, college deferments were allowed, and draftees were significantly more likely to obtain conscientious objector status as well. Differences between those who served in the Korean War and their counterparts who did not serve are therefore less clear. In addition, while Korean War veterans received largely the same G.I. Bill benefits as WWII veterans, their military service was likely to have been viewed and treated differently by the public given that support for the Korean War was more ambiguous than support for WWII.

4.5 Intergenerational Data

A range of previous studies has attempted to estimate the effect of changes in parental characteristics on children's outcomes. These studies have used a wide range of datasets, from the National Academy of Sciences-National Research Council (NAS-NRC) sample of twins (Behrman & Taubman, 1989) to large sets of Korean American adoptees (Sacerdote, 2007). One commonality of these many sources of data, however, is that they lack the detailed information on parental military service needed to analyze its effects on children.

Some researchers have used panel data on families from the National Longitudinal Surveys of Youth (NLSY) and Panel Study of Income Dynamics (PSID) to examine intergenerational linkages. For example, Rosenzweig & Wolpin (1994) use a sample of mothers and children from the NLSY to provide evidence that increased maternal schooling leads to greater academic achievement by children. Studies of intergenerational income mobility (for example, Behrman & Taubman (1990)) have often used the PSID. However, while these surveys collect information on military service, neither the PSID nor the modern cohorts of the NLSY contains data on sufficient numbers of Baby Boomer children and their parents. Data from a series of similar surveys of the NLS Original Cohorts may contain fathers and children from appropriate periods. However, father characteristics can only be obtained for those children in these cohorts whose fathers were born between 1907 and 1921. These fathers likely represent an unrepresentative subset of fathers of Baby Boomer children, most importantly because members of many of these cohorts were relatively unlikely to have served in the military. Moreover, the NLS Original Cohorts do not provide a very large set of fathers linked to children.

An appropriate dataset to examine the relationship between fathers' military service and childrens' educational attainment must link children to their fathers and contain detailed information on fathers' military service, childrens' educational attainment, and a host of other family characteristics. Oreopoulos et al. (2006) propose a method of examining intergenerational effects on children's education using cross-sectional Census data, which is adopted for this study. This methodology has inherent limitations, but it allows for examination this issue using a large set of fathers and children. Moreover, using the Census enables this analysis to leverage the military service information collected for fathers.

While fathers and children who have left the household cannot be linked in the U.S. Census, fathers can be matched to children so long as both remain in the household. Therefore, large numbers of young children can be linked to fathers who live with them. Because most of the children living in their parents' households are young, this necessarily means that there are no data on ultimate high school graduation and postsecondary educational attainment. [3] However, for these younger children, it is possibnle to generate a measure of relative educational progress adapted from that proposed by Oreopoulos et al. (2006). Using the set of all children in the sample, the median grade completed by those born in the same quarter is calculated by state of residence. Each child's last completed grade is then compared to the median for her cohort. Children at or above this median are judged to be at the appropriate grade for age.

Oreopoulos et al. (2006) and Page (2006) intend this measure to be a rough proxy for grade repetition, which is in turn predictive of ultimate educational attainment. A validation study by Cascio (2005) using more recent data from the Current Population Survey finds that 21% of those who did not repeat a grade are classified as below grade, while 12% of repeaters are classified as being at the appropriate grade. Historical Census data like those used here likely exhibit similar systematic misclassification errors. But by using this measure as the dependent variable for this analysis, the impact on a child's educational progress relative to

[3]The linking process also yields the necessary limitation that only children with fathers present are included in the estimation sample. Differences between all children in the Census and those linked to fathers and therefore included in the estimation sample are shown in Appendix B.

her peers is explicitly modeled, both as a result of grade repetition and as a result of other factors. This is in contrast to absolute measures of educational attainment such as high school or college graduation, and to direct measures of grade retention which are not available for this sample.

This measure is comparable to that derived from the National Assessment of Educational Progress (NAEP), administered by the National Center for Education Statistics. Publicly available NAEP data are not available at the state level; the most granular geographic measure is one of nine Census districts. Table 15 compares measures of grade-for-age from the 1970 Census to those from the 1970-1971 NAEP. Younger children are more likely to be at grade for age in both samples. Calculating the grade for age measure at a more aggregated level increases the percent of children at grade for age. This measure lines up closely for the 13-year-old NAEP sample (both 80.0%), while the 9-year-old sample is similar, though not an exact match (84.5% and 86.0%).

Table 15. Census and NAEP Measures: Percent of Children at Grade for Age

	1970 Census		1970-1971 NAEP
Geographic level calculated:	State	Census district	Census district
Entire sample of children	80.4%	80.8%	
9-year-olds	82.9%	84.5%	86.0%
13-year-olds	77.6%	80.0%	80.0%

Notes: Percentages are weighted using provided sampling weights. Samples of 9- and 13-year-olds mirror the NAEP samples as closely as possible; "9-year-olds" from Census are those born in 1961 and "13-year-olds" are born in 1956.

This analysis uses the IPUMS (Ruggles et al., 2010) 1% sample of the 1970 U.S. Census[4] to construct a sample of Baby Boomer children in households with fathers. Fathers are linked to Baby Boomer children between the ages of 7 and 15 in the same household. This yields a sample of children born from April 1954 to March 1963, covering a significant portion of the Baby Boomer generation. The sample is limited to nonfarm households containing fathers and children born in the U.S., without allocated values for race, sex, age, or father's veteran status. Aditionally, children are only linked to fathers who are at least 18 years older than their children.

To simplify this analysis, it is limited to examining only children of white fathers. This stems from starkly different experiences likely felt by nonwhite soldiers both during and after military service. During WWII, the armed forces were segregated; Harry S. Truman issued an executive order ending this segregation in 1948. Intense discrimination persisted throughout the Korean War. As a result, the experience of nonwhite soldiers was likely very different from that of white soldiers. Moreover, the effect of service may have been significantly different for nonwhite soldiers. For example, Turner & Bound (2003) find that the G.I. Bill had little effect on the educational attainment for blacks in the South. Similarly, racial discrimination in housing markets remained a significant problem for decades after WWII. Collins & Margo (2001) note that the "VA explicitly included race as a criterion in their appraisal process," and red-lining remained a common practice in housing markets until at least the passage of fair housing legislation in 1968. For all of these

[4]IPUMS provides multiple samples of the 1970 Census; only the 1% Form 2 State sample is used, since this is the only sample to contain both detailed military service information and identifiers for the state of residence of all respondents.

reasons, the effects of service on nonwhite veterans and their families are beyond the scope of this analysis.

This sample of linked children is used to produce two estimation samples based on cutoffs used in analyses by Fetter (2013). The first is a sample of children linked to fathers from birth cohorts before and after January 1, 1928, which coincided with a dramatic dropoff in participation in WWII. This WWII generation of fathers includes those born from 1925 to 1930, excluding the fourth quarter of 1927 and the first quarter of 1928. Similarly, the second sample, the Korean War generation, includes children with fathers born in the three years before and after January 1, 1934, excluding the fourth quarter of 1933 and the first quarter of 1934. Basic characteristics of children in these estimation samples are shown in Table 16.

Table 16. Sample Characteristics

	WWII Generation	Korean War Generation
Age	11.44	10.48
Family size	5.77	5.70
Family owns home	84.4%	80.0%
At grade for age	81.8%	81.7%
Number of observations	60,843	60,965

Notes: Samples of Baby Boomer 7-15 year olds constructed from 1970 IPUMS 1% sample using restrictions given in text.

The IPUMS data contain extensive information on parental characteristics. Of primary importance is the suite of military service indicators in IPUMS. Male Census respondents are asked if they served in the military, and if so, during which periods. This information is used to construct indicators of all service and of service in the World War II and Korean War periods.[5]

Additional parental characteristics include age, homeownership, and education. Fathers report year and quarter of birth, which are used to calculate age and birth cohort. Household-level information on homeownership is used to construct an indicator of whether a household owns its home (as opposed to renting). Fathers report their last completed year of education. From this, indicators for high school and college graduates are constructed, keeping in mind that the data do not contain direct graduation information. With this caveat, however, these serve as measures of overall educational attainment.

Table 17. Father Characteristics: Linked 7-15 year olds in 1970

	WWII Generation	Korean War Generation
Mean		
Age	41.5	35.9
Family size	5.8	5.7
Percent		
Married	98.9%	99.2%
Own home	84.4%	79.9%
Military veteran	78.6%	62.4%
World War II veteran	42.3%	0.0%
Korean War veteran	38.1%	48.2%
High school graduate	65.2%	69.0%
College graduate	21.5%	18.3%
Number of observations	60,843	60,965

Notes: Samples of Baby Boomer 7-15 year olds linked to fathers in same households constructed from 1970 IPUMS 1% sample using restrictions given in text.

[5]The World War II and Korean War periods specified in the Census correspond to the periods of service conferring eligibility for GI Bill benefits, provided that a veteran served 90 days in the appropriate period and received an honorable discharge.

These father characteristics are summarized in Table 17. Fathers in the sample are, on average, approximately 30 years older than the children to whom they are linked. Since fathers must be in the household with their children to be linked and the vast majority of children to unwed parents would live with the mother, almost all of the children linked to fathers in this way have married fathers.[6]

4.6 Linear Probability Model Estimates

This section examines whether the educational progress of the Baby Boomer children in these samples was correlated with their fathers' veteran status. It also investigates whether that correlation was related to veteran status alone, or to home-ownership and father's education level, both characteristics that were subsidized for veterans after their service. To do so, linear probability models of the propensity to be at grade for age are estimated, controlling for a variety of measurable factors that would be expected to be related to educational progress.

The basic regression framework is intended to estimate the educational progress of children, controlling for basic child characteristics related to educational outcomes. The dependent variable used is the measure of whether a child is at grade for age. Linear probability models are estimated of the form:

$$AtGradeForAge_i = \alpha + \beta VetFather_i + \gamma X_i + \delta Y_i + \epsilon_i \tag{4.1}$$

where X_i is a vector of controls for the child's age, birth quarter, and sex. All of these control variables take the form of indicator variables. For each model, add sets of controls are then added as the vector Y_i. First, controls for family size and

[6] However, it should be noted that linked families were of similar size to all families in the sample with children of appropriate ages, as shown in Table 25.

the father's marital status are added. Then, separate controls for homeownership and the education level of the father are added, in the form of indicator variables for high school and college graduation. Finally, the model is estimated with all controls.

The age of a child's father likely plays a significant role in her childhood experiences, and this relationship may be highly nonlinear in father's age. Age is controlled for in a minimally parametric way by including indicator variables for each possible birth year of fathers.

Table 18. Educational Progress Gap for Children of Veterans and Nonveterans: Pooled OLS Results

	Model					
Sample	(1)	(2)	(3)	(4)	(5)	Sample Size
WWII Generation	.044	.024	.017	.020	.014	60,843
	(.004)	(.004)	(.004)	(.004)	(.004)	
Korean War Generation	.022	.007	.002	.003	-.001	60,965
	(.003)	(.003)	(.003)	(.003)	(.003)	
Family Characteristics	No	Yes	Yes	Yes	Yes	
Father's Education	No	No	Yes	No	Yes	
Homeownership	No	No	No	Yes	Yes	

Notes: Samples of 7-15 year old Baby Boomer children and their fathers constructed from 1970 IPUMS 1% sample using restrictions given in text. The educational progress gap is the difference in proportion of children of veterans at grade for age relative to children of nonveterans. All models include controls for age and birth quarter of child and indicator variables for each birth year of fathers. "Family characteristics" are controls for father's marital status, family size, and father's spouse's age and education level where appropriate. Robust standard errors are in parentheses.

Results for these models estimated using pooled data from all fathers and children in each sample are shown in Table 18. In both samples, children of veterans are significantly more likely than children of nonveterans to be at or above grade level for age. The difference in educational progress is attenuated slightly by controlling for family size and father's marital status. It is reduced more significantly by controlling for father's educational attainment and homeownership. However, in both samples a significant gap in educational progress remains even after controlling for all of these characteristics.

These estimated effects on educational progress are sizable relative to the incidence of children below grade for age: 18% of children in the WWII sample and 17% of children in the Korean War sample. In this context, an association of over four percentage points in the absence of controls for the WWII sample represents a significant reduction in the proportion of children below median grade level for their age. Even the estimated association of nearly two percentage points found when controlling for all covariates is a meaningful shift in children's educational progress in this context. By contrast, the observed effects in the Korean War sample are smaller, and the effect is not significantly distinguishable from zero when a full suite of controls is included.

To further examine the sensitivity of the model to this method of controlling for father's age, this analysis adopts the approach that Angrist & Krueger (1994) used as a first step in analyzing the difference in wages for World War II veterans relative to nonveterans: a separate regression model is estimated for each birth year of fathers. This is equivalent to fully interacting all controls with father's age. The results are shown in Table 19 for the WWII sample, echoing the results of the pooled model. However, the observed effect is much larger for fathers born before 1928. In each year before 1928, a gap of at least five percentage points is present before the addition of controls beyond the basic controls for child's age, birth quarter, and sex.

This gap consistently narrows with controls for family characteristics, father's education, and homeownership; as in the pooled model, however, a gap remains across cohorts of fathers even controlling for these factors. This gap is only statistically significant for fathers born before 1928, once all controls are included in the model.

Table 19. Educational Progress Gap for Children of Veterans and Nonveterans: OLS Results, WWII Generation

	Model					
Father's Birth Year	(1)	(2)	(3)	(4)	(5)	Sample Size
1925	.093	.055	.046	.050	.042	9,230
	(.013)	(.012)	(.012)	(.012)	(.012)	
1926	.052	.031	.023	.026	.019	9,640
	(.012)	(.012)	(.012)	(.012)	(.012)	
1927	.069	.042	.035	.040	.034	8,396
	(.013)	(.012)	(.012)	(.013)	(.013)	
1928	.034	.017	.010	.014	.007	8,710
	(.010)	(.009)	(.009)	(.009)	(.009)	
1929	.032	.013	.008	.010	.006	12,281
	(.008)	(.008)	(.008)	(.008)	(.008)	
1930	.028	.014	.007	.010	.003	12,586
	(.008)	(.008)	(.008)	(.008)	(.008)	
Family Characteristics	No	Yes	Yes	Yes	Yes	
Father's Education	No	No	Yes	No	Yes	
Homeownership	No	No	No	Yes	Yes	

Notes: Samples of 7-15 year old Baby Boomer children and their fathers constructed from 1960 and 1970 IPUMS samples using restrictions given in text. The educational progress gap is the difference in proportion of children of veterans at grade for age relative to children of nonveterans. All models include controls for age and birth quarter of child. "Family characteristics" are controls for father's marital status and family size. Robust standard errors are in parentheses.

4.7 Propensity Score Matching Estimates

An alternative method to estimate the treatment effect of fathers' military service on childrens' educational progress is to match children in the treatment and control groups using propensity score matching. This allows for controlling for observable differences in a minimally parametric way, and once these factors have been controlled across the two samples, the remaining overall effect on children's educational progress can be estimated. The primary drawback of this approach is that, like the linear probability models, it is unable to control for unobserved differences between the treatment and control groups. However, to the extent that the major factors involved are are observable and can be controlled for, propensity score matching can provide further evidence of a relationship between military service and children's educational progress.

The propensity score matching process has two components. First, the propensity score, representing the probability that a child's father is a military veteran, is estimated using a probit model of military service as a function of indicator variables for observable controls. As with the linear probability models, three models are used. The first contains controls for family size; father's birth cohort, birth state, and marital status; for married fathers, the mother's age and educational attainment; and the child's age, birth quarter, and gender. The second propensity score probit regression adds to these variables an indicator for the father's educational attainment. Finally, the third model contains all of these controls plus an indicator of homeownership status.

For the second component of this process, 1-to-1 matching on the propensity score is used to match children whose fathers are military veterans to those who are not. The characteristics of matched and unmatched samples using the full suite of controls are shown in Tables 20 and 21. As shown in these tables, this process eliminates much of the observable differences in characteristics.

Table 20. Effect of Matching on Sample Characteristics, WWII Generation

	Original Sample			Matched Sample		
	Children of Non-veterans	Children of Veterans	p-value of difference	Children of Non-veterans	Children of Veterans	p-value of difference
Family size	5.60	5.46	<.001	5.42	5.46	.046
Homeowner	77.7%	86.2%	<.001	85.5%	86.2%	.119
Child						
age	11.49	11.43	.015	11.46	11.42	.895
female	48.8%	48.8%	.893	49.2%	48.8%	.849
Father						
married	98.6%	98.9%	.002	99.0%	98.9%	.822
HS grad	52.7%	68.7%	<.001	68.1%	68.7%	.349
college grad	16.1%	23.0%	<.001	21.3%	23.0%	.007
Father's spouse						
age	37.54	38.01	.002	37.92	38.01	.367
HS grad	59.2%	72.7%	<.001	72.9%	72.7%	.789
college grad	7.7%	10.2%	<.001	9.8%	10.2%	.366

Notes: Samples of 7-15 year old Baby Boomer children and their fathers constructed from 1970 IPUMS sample using restrictions given in text.

Table 21. Effect of Matching on Sample Characteristics, Korean War Generation

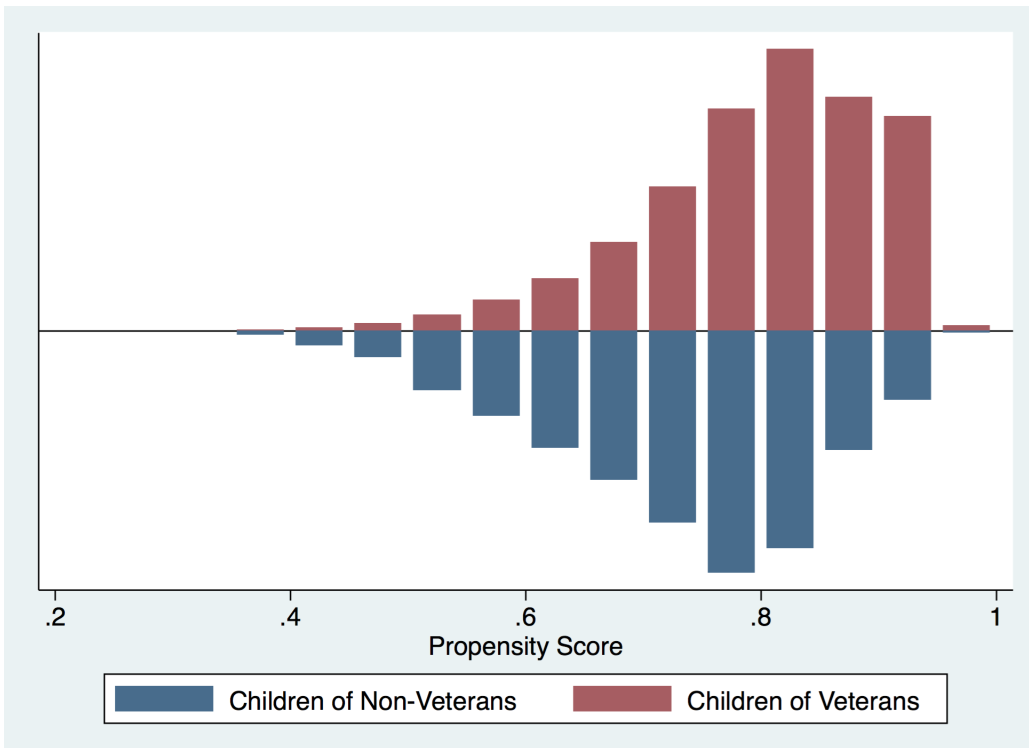
	Original Sample			Matched Sample		
	Children of Non-veterans	Children of Veterans	p-value of difference	Children of Non-veterans	Children of Veterans	p-value of difference
Family size	5.59	5.43	<.001	5.44	5.43	.627
Homeowner	74.8%	83.0%	<.001	81.6%	83.0%	.003
Child						
age	10.73	10.33	.000	10.30	10.33	.301
female	48.1%	49.0%	.036	48.6%	49.0%	.533
Father						
married	98.9%	99.4%	<.001	99.4%	99.4%	.439
HS grad	61.1%	73.8%	<.001	73.4%	73.8%	.408
college grad	16.2%	19.6%	<.001	19.5%	19.6%	.890
Father's spouse						
age	33.03	33.64	<.001	33.80	33.64	.007
HS grad	62.3%	73.5%	<.001	73.1%	73.5%	.441
college grad	5.5%	7.7%	<.001	8.2%	7.7%	.233

Notes: Samples of 7-15 year old Baby Boomer children and their fathers constructed from 1970 IPUMS sample using restrictions given in text.

The distributions of propensity scores using the full suite of controls are shown in Figures 11 and 12. The distributions are nearly identical for the other sets of models. As shown in Figure 11, children of WWII veterans on average have characteristics more likely to be associated with veteran fathers, resulting in higher propensity scores. While there is a small difference in the distributions of propensity scores for children of veterans and non-veterans in the WWII generation, the difference for the Korean War generation, seen in Figure 12, is more dramatic.

After matching the samples, the average treatment effect is calculated as the difference in the proportion of children at grade for age between the two matched samples. The estimated average treatment effects are shown in Table 22 and mirror those from the linear probability models. For the WWII sample, the average treatment effect for model (1) is about 2.5 percentage points, in line with the linear probability model estimates. Adding controls for fathers' education reduces the observed effect to 1.6 percentage points, and further adding homeownership reduces the effect to 0.9 percentage points; however, all of these estimated effects are statistically significant at the 5% level.

Figure 11. Propensity Score Distributions, WWII Generation



By contrast, the average treatment effect for the Korean War sample is statistically significant only when controls for fathers' education are not included. This suggests that much of the observed relationship may be due to resulting increases in fathers' education after military service.

Figure 12. Propensity Score Distributions, Korean War Generation

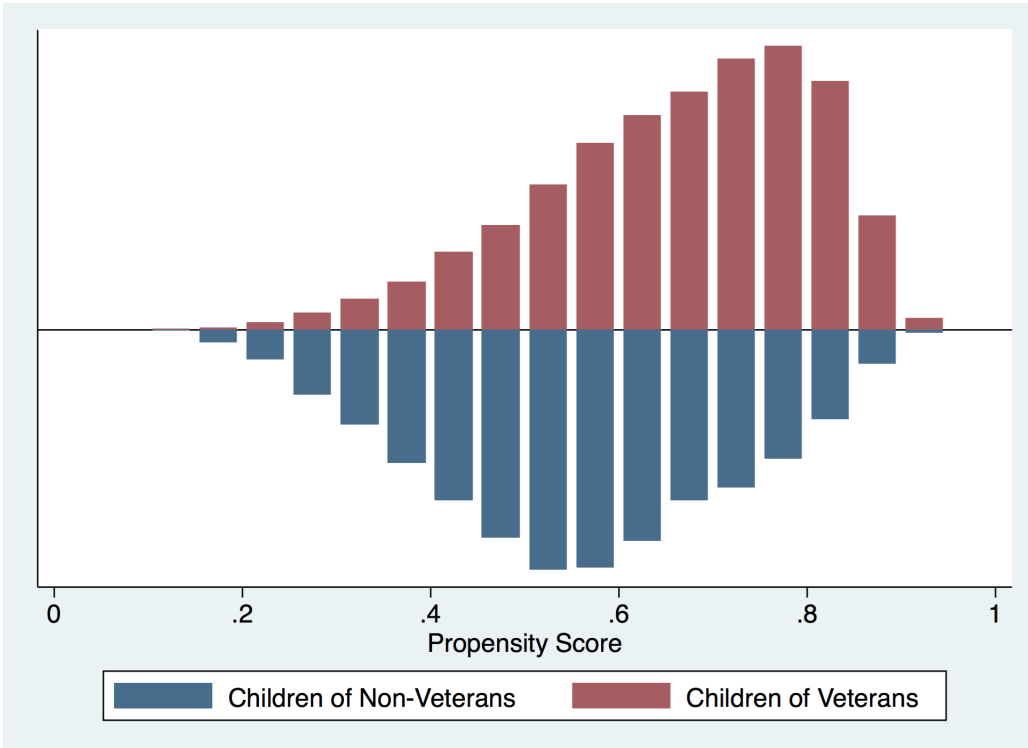


Table 22. Relative Educational Progress for Children of Veterans: Propensity Score Matching Results

	World War II Generation			Korean War Generation		
Model:	(1)	(2)	(3)	(1)	(2)	(3)
Veteran father	.025	.016	.009	.008	.001	-.003
	(.005)	(.005)	(.005)	(.004)	(.004)	(.004)
Family Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Father's Education	No	Yes	Yes	No	Yes	Yes
Homeownership	No	No	Yes	No	No	Yes
Sample size	60,843	60,843	60,843	60,965	60,965	60,965

Notes: Samples of 7-15 year olds constructed from 1970 IPUMS sample using restrictions given in text. Nearest neighbor matching performed within father's birth quarter cohort. Propensity score is calculated using indicators for child's age, birth quarter, and gender; father's birth state, and marital status; father's spouse's age and education level where appropriate; and family size. Model (2) adds indicator variables for father's educational attainment. Model (3) also adds an indicator variable for homeownership.

In summary, the propensity score matching estimates echo the linear probability model estimates. These models yield estimates of modest effects on relative education progress when controls for many observables–but not father's education and homeownership–are included, ranging from 0.8 percentage points for the Korean War generation to 2.5 percentage points for the WWII generation. When additional controls for education are included, the estimated effect decreases to approximately zero for the Korean War generation and 1.6 percentage points for the World War II generation. Inclusion of homeownership controls further reduces the estimated effect. As noted in Section 4.3.2 above, controlling for homeownership may in fact produce a biased estimate of the effect of military service. But even controlling for homeownership, propensity score matching yields a positive estimated effect of military service in WWII.

4.8 Regression Discontinuity Estimates

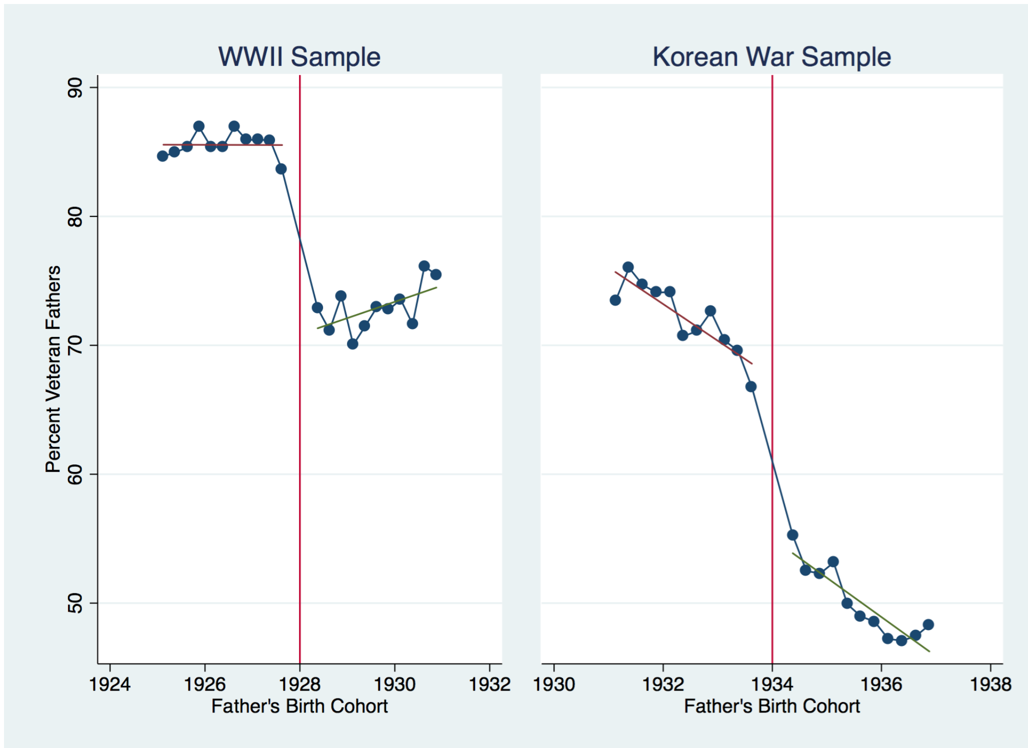
Military service does not represent an ideal natural experiment, since selection into service in World War II and the Korean War was nonrandom. However, a range of previous studies has taken advantage of cross-cohort variation in levels of service to estimate exogenous effects of service in these wars on various outcomes.

For example, Angrist & Krueger (1994) examine effects of World War II service on income. They find sizable positive effects of World War II service on income using OLS. They use variation in service rates across birth quarters as a result of the use of birthdate in the draft from 1925 to 1928 to instrument for service. Using these IV models, they find evidence of a negative or zero effect on income.

Yamashita (2008) uses a similar approach of instrumenting for service using quarter of birth to examine impacts on veteran homeownership, finding significant positive effects on homeownership for white veterans. By contrast, Fetter (2013) analyzes effects on homeownership but uses a regression discontinuity approach. He relies on two major discontinuities in military service: for those with birth dates before and after January 1, 1928 and January 1, 1934. Like Yamashita, Fetter finds significant impacts on homeownership.

Bound & Turner (2002) use similar methods to estimate impacts on educational attainment. They effectively instrument for veteran status using quarter of birth dummies by aggregating at the birth cohort level. Additionally, they use one of the discontinuities identified by Fetter as an instrument. Using these models, they estimate a positive effect of veteran status on postsecondary education.

Figure 13. Proportion of Sample Children Fathers with Military Service



Source: Samples of 7-15 year olds constructed from 1970 IPUMS 1% sample using restrictions given in text.

4.8.1 Regression Discontinuity Approach

There is evidence of a significant break in the data, as shown in Figure 13. The two panels show the data series of the percent of veteran fathers used in final model estimation, along with vertical lines at the cutoff (January 1, 1928 or January 1, 1934) and fitted lines for the portion of the series before and after the cutoff. It is important to note that while the dropoff in military service rates is significant at these time points, it is not complete.

Imbens & Lemieux (2008) distinguish between two possible regression discontinuity scenarios, sharp regression discontinuity (SRD) and fuzzy regression discontinuity (FRD). In a SRD scenario, treatment is completely determined by a predictor variable; one example would be a policy which only applies to firms with 15 employees. By contrast, in a FRD scenario the predictor does not completely determine treatment, as seen here.

The coefficient of interest, τ, is then estimated as the ratio of the change in the dependent variable over the change in the indicator variable:

$$\hat{\tau}_{FRD} = \frac{\hat{\tau}_y}{\hat{\tau}_w} = \frac{\hat{\alpha}_{yr} - \hat{\alpha}_{yl}}{\hat{\alpha}_{wr} - \hat{\alpha}_{wl}} \tag{4.2}$$

where $\hat{\alpha}_{yl}$ is the estimated effect, using local linear regression, for the outcome variable on the left side of the discontinuity point, $\hat{\alpha}_{wl}$ is the estimated effect for the treatment variable on the left side of the discontinuity point, and $\hat{\alpha}_{yr}$ and $\hat{\alpha}_{wr}$ are the corresponding estimates on the right side.

Imbens & Lemieux (2008) demonstrate that in the case of a uniform kernel calculated with the same bandwidth on each side of the discontinuity, the estimator for the effect of interest τ is simply the TSLS estimator with the indicator variable $1\{X_i \geq c\}$ as the excluded instrument. This extends the equality noted by Hahn et al. (2001)–under the restriction of no additional covariates–to the more general case of additional covariates. As such, these three methods of calculating $\hat{\tau}_{FRD}$ are equivalent:

(1) The ratio of effects estimated using local linear regression on each side of the discontinuity,

(2) Kernel estimation using a uniform kernel calculated with the same bandwidth on each side of the discontinuity, and

(3) The TSLS estimator with the indicator variable $1\{X_i \geq c\}$ as the excluded instrument.

This analysis takes a strategy similar to that of Fetter (2013), representing the third method. It focuses on two birth dates after which cohort military service rates drop dramatically: January 1, 1928 and January 1, 1934. For each, data from cohorts within three years of the break point are used, excluding the cohorts before and after the break point; this is the same sample used for OLS models above.

Two-stage least squares is used to estimate the models, specifying a first stage allowing for separate linear trends before and after the break point:

$$\begin{aligned} VetFather_i = \alpha &+ \beta\mathbf{1}(FC_i < c) + \gamma\mathbf{1}(FC_i < c)(FC_i - c) \\ &+ \delta\mathbf{1}(FC_i > c)(FC_i - c) + \lambda X_i + \epsilon_i \end{aligned} \tag{4.3}$$

for a child with father in father cohort FC with relevant cutoff c, with indicators $\mathbf{1}(FC < c)$ for father's birth before the cutoff and $\mathbf{1}(FC > c)$ for father's birth after the cutoff. The excluded instrument is then the indicator $\mathbf{1}(FC_i < c)$. X_i is a vector of controls, containing in all models child's age and birth quarters, and in some models the father's marital status and family size. The $VetFather$ is an indicator for whether the child's father is a veteran.

The second stage estimates the child's at-grade-for-age status using the father's predicted veteran status from the first stage, again allowing for linear trends in the father's cohort before and after the cutoff:

$$AtGradeForAge_i = \alpha + \beta VetFather_i + \gamma \mathbf{1}(FC_i < c)(FC_i - c) \\ + \delta \mathbf{1}(FC_i > c)(FC_i - c) + \lambda X_i + \epsilon_i \tag{4.4}$$

4.8.2 Results

Table 23. Relative Educational Progress for Children of Veterans: Regression Discontinuity Results

	World War II Cutoff		Korean War Cutoff	
Model:	(1)	(2)	(1)	(2)
Veteran father	.166	.416	.131	.152
	(.288)	(.328)	(.053)	(.052)
First stage F statistic on excluded instrument	11.00	9.65	1.25	1.93
Sample size	60,843	60,843	60,965	60,965

Notes: Samples of 7-15 year olds constructed from 1970 IPUMS sample using restrictions given in text. Model (1) contains controls for child's sex, age in years, and birth quarter as well as separate linear trends in father's birth cohort before and after the cutoff. Model (2) adds controls for family size and father's marital status. Robust standard errors are in parentheses.

Using the regression discontinuity approach yields sufficiently strong instruments in the WWII cutoff sample, as shown by the first stage F statistic on the excluded instrument. However, the estimated standard errors are extremely large, so that no practical effect could be statistically distinguished from zero.

By contrast, around the Korean War cutoff, the regression discontinuity yields statistically significant positive effects. However, these estimates suffer from weak instrument problems, with the first stage F statistic on the instrument below 2 in both models. While a large and statistically significant effect is estimated using these models, the weakness of the instrument suggests that this estimate is significantly biased. Taken together across both samples, the regression discontinuity approach does not produce sufficiently precise estimates to draw conclusions, but these estimated effects are in line with the linear probability model and propensity score matching results.

4.9 Conclusions

The question of whether fathers' military service impacted Baby Boomer children's educational attainment is a difficult one to answer given the challenges posed by available data and selection into military service. Borrowing heavily from previous work on intergenerational effects of parental education, this study compiles a set of Baby Boomer children linked to their fathers from Census data. These data provide evidence in linear probability models that a father's military service in World War II or the Korean War is associated with increased educational progress by his children relative to their peers. Observed differences in family characteristics, homeownership, and educational attainment by veteran fathers explain some, but not all, of this gap.

Controlling for characteristics associated with selection into military service in an alternative way with propensity score matching, this analysis finds consistently statistically significant effects across models and samples. A father's military service is estimated with these models to have a positive effect on the child's probability of being at grade for age of between about one and 2.5 percentage points. As with linear probability models, these associations decrease when controls for education and homeownership are included, though the effects remain positive and statistically significant for WWII veterans.

Using regression discontinuity methods modeled on and expanding upon previously used approaches, weak instruments are encountered across an array of models. While an IV model using cross-cohort variation in service rates estimates positive effects of fathers' military service, this effect is not robust to specification of nonlinear trends in fathers' age. On the whole, these models are unable to estimate effects on children's educational progress of the modest size estimated using OLS and propensity score matching models. Therefore, while this analysis has shown evidence of a positive relationship between fathers' military service and children's educational progress, it is unable to draw strong conclusions regarding the impact of selection into military service.

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APPENDIX A

ADDITIONAL CHARACTERISTICS OF THE ATUS SAMPLE

Table 24. Additional Sample Characteristics

	Full Sample	Men	Women
Occupation Categories			
Management	13.4%	14.5%	12.0%
Business and financial operations	6.6%	5.2%	8.4%
Computer and mathematical science	4.2%	5.7%	2.1%
Architecture and engineering	3.2%	4.9%	1.0%
Life, physical, and social science	1.4%	1.3%	1.6%
Community and social service	2.2%	1.4%	3.2%
Legal	1.4%	1.1%	1.9%
Education, training, and library	6.9%	3.5%	11.5%
Arts, design, entertainment, sports, and media	1.6%	1.6%	1.7%
Healthcare practitioner and technical	4.5%	2.2%	7.5%
Healthcare support	1.5%	0.3%	3.0%
Protective service	1.7%	2.4%	0.8%
Food preparation and serving related	2.0%	1.9%	2.1%
Building and grounds cleaning and maintenance	3.0%	3.7%	2.1%
Personal care and service	1.2%	0.7%	2.0%
Sales and related	8.1%	9.1%	6.8%
Office and administrative support	14.3%	6.3%	24.9%
Farming, fishing, and forestry	0.6%	0.8%	0.3%
Construction and extraction	5.5%	9.5%	0.3%
Installation, maintenance, and repair	4.7%	7.8%	0.5%
Production	7.4%	9.5%	4.6%
Transportation and material moving	4.5%	6.7%	1.6%
Industry Categories			
Agriculture, forestry, fishing, and hunting	0.8%	1.2%	0.3%
Mining	0.6%	1.0%	0.2%
Construction	6.7%	10.9%	1.2%
Manufacturing - durable goods	9.7%	12.6%	5.8%
Manufacturing - non-durable goods	5.3%	6.1%	4.2%
Wholesale trade	3.6%	4.4%	2.5%
Retail trade	7.8%	8.6%	6.8%
Transportation and warehousing	3.7%	4.9%	2.1%
Utilities	1.5%	2.3%	0.6%
Information	3.0%	3.2%	2.7%
Finance and insurance	7.6%	5.6%	10.1%
Real estate and rental and leasing	1.7%	1.9%	1.5%
Professional, scientific, and technical services	7.5%	7.9%	7.0%
Management, administrative and waste management services	3.6%	4.1%	2.9%
Educational services	10.6%	6.1%	16.5%
Health care and social services	12.1%	5.2%	21.2%
Arts, entertainment, and recreation	1.1%	1.1%	1.0%
Accommodation and food services	3.1%	3.1%	3.2%
Private households	0.2%	0.0%	0.4%
Other services, except private households	3.4%	3.9%	2.7%
Public administration	6.5%	5.9%	7.3%

Source: ATUS 2003-2014 samples with restrictions as noted in text. Sample percentages are weighted using ATUS respondent probability weights.

APPENDIX B

CHARACTERISTICS OF LINKED AND UNLINKED CHILDREN

As shown in Table 25, the samples of children linked to their father are similar to the entire samples of children of the appropriate ages in 1970. The linked children are, on average, slightly more likely to be at or above the median grade for their age cohorts and to live in homeowning households. Linked children are nearly identical in age and have similar numbers of family members living in their households relative to all children in the sample.

Table 25. Sample Characteristics: All 1970 Sample 7-15 year olds and those Linked to Fathers

	All Children	Linked Children
Age	10.95	10.97
Family size	5.67	5.54
Family owns home	77.9%	81.3%
At grade for age	80.4%	81.5%
Number of observations	269,006	218,141

Notes: Samples of Baby Boomer 7-15 year olds constructed from 1970 IPUMS 1% sample using restrictions given in text.